The Dissertation Committee for Jessica Ann Cooper Certifies that this is the approved version of the following dissertation:

Attenuating Reflexive and Reflective Decision Making Deficits Through Targeted Training

Committee:

Christopher G. Beevers, Supervisor

Bharath Chandrasekaran

David M. Schnyer

Darrell A. Worthy

Attenuating Reflexive and Reflective Decision Making Deficits Through Targeted Training

by

Jessica Ann Cooper, B.A.

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Dedication

This dissertation is dedicated to my mother, who taught me that science could be fun.

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Attenuating Reflexive and Reflective Decision Making Deficits Through Targeted Training

Jessica Ann Cooper, Ph.D.

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Supervisor: Christopher G. Beevers

Contemporary learning theories posit the existence of at least two distinct systems that mediate learning. These systems are recognized under the dual-learning systems (DLS) hypothesis as a *reflective* system that is available to conscious awareness and that uses working memory resources to develop and test hypotheses, and a *reflexive* system that is not available to conscious awareness and that depends on learning via reinforcement. Depression is associated with impairments in reflexive processes, including blunted implicit reward sensitivity and biased attention to negative information, and impairments in reflective processing, including declines in working memory, planning, and problem solving. We hypothesize that these deficits contribute to observed differences in decision-making performance associated with depression. In this series of work we explore the effects of sub-clinical symptoms of depression on decision-making performance and use the dual-learning systems hypothesis to develop targeted training mechanisms to modify behavior in two types of decision-making tasks.

In order to effectively develop mechanisms to modify performance, we must understand the cognitive processes and strategies that are necessary for optimal task performance. In Chapters 1 and 2 we identify two types of decision-making tasks for which reflective and reflexive strategies differentially affect performance. The reflective

task is a history-dependent decision-making task for which short-term rewards must be foregone to maximize long-term performance. The reflexive task is a history-independent decision-making task for which one option gives a higher average reward and rewards are only dependent on the most recent response. Chapters 3 and 4 confirm deficits associated with elevated symptoms of depression in both of these tasks and test the effects of attention and working-memory training paradigms on modifying behavior. These chapters focus on inducing short-term improvements in decision-making by modifying the strategies that participants engage.

Whereas much of this work explores short-term training with a goal of temporarily improving processing in individuals with elevated symptoms of depression, Chapter 5 uses long-term working memory training with a goal of producing persisting changes in cognitive processing. Implications for future work are discussed.

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OVERVIEW AND BACKGROUND

From financial choices to lifestyle and health decisions, weighing the value of different options and making choices is a necessary part of our day-to-day activity. Reward processing is critical to many of these decisions, and deficits in reward processing could be devastating to a person's quality of life. Many individuals have difficulty with reward processing and decision-making, in particular those with major depressive disorder and elevated depressive symptoms (i.e. Beevers et al., 2013; Eshel & Roiser, 2010; Maddox, Gorlick, Worthy & Beevers, 2012; Pizzagalli et al., 2009).

Much research suggests that there are at least two dissociable and neurobiologically-grounded learning systems: a reflective, hypothesis-testing system, and reflexive, procedurally-based system. These systems likely use reward information differently, and we need to understand similarities and differences in reward processing across these two systems. We can then use knowledge of the systems to develop interventions to reduce deficits that are associated with depression.

DUAL-LEARNING SYSTEMS THEORY

This series of studies examines different types of decision-making tasks under the dual-learning systems hypothesis, which posits that learning involves a competition between *reflective* and *reflexive* cognitive systems. An extensive body of behavioral and neuroimaging studies have explored these competing learning systems (Ashby & Maddox, 2005; Ashby & Maddox, 2011; Blanco, Otto, Maddox, Beevers, & Love, 2013; Chandrasekaran, Yi, & Maddox, 2014; Daw, Niv, & Dayan, 2005; Knowlton, 1999; Knox, Otto, Stone, & Love, 2012; Maddox & Ashby, 2004; Nomura et al., 2007; Poldrack & Packard, 2003). The reflective learning system uses working memory and executive attention to develop and test verbal rules (i.e. Maddox & Ashby, 2004). In contrast, the reflexive learning system is not dependent on working memory and executive attention (DeCaro, Thomas & Beilock, 2008) and operates by forming automatic associations with actions that lead to reward (Seger, 2008; Seger & Cincotta, 2005; Seger & Miller, 2010).

It should be noted that the reflective/reflexive distinction in decision-making is similar to the model-based/model-free distinction (Daw et al., 2005; Doya et al., 2002; Glascher, Daw, Dayan, & O'Doherty, 2010). In model-based systems, decision-makers build cognitive maps or models of the environment that relate different ''states'' of the reward environment to each other. Decision-makers using model-free learning systems learn action values directly, by trial and error, without forming an explicit representation of the reward environment (Daw et al., 2005). While similar to the model-based/model-free distinction, our distinction between reflective and reflexive processing is different in that reflective processing is defined by the use of working memory and executive processing to inform decisions, even if the strategy is only a simple heuristic-based process. While engaging reflective processes, individuals do not necessarily have to form an explicit model or representation of the underlying reward structure.

Engagement of the reflective and reflexive learning systems often leads to different behavioral results and has also been associated with different neural regions that support their differentiation. Processing in the reflective system is available to conscious awareness and is mediated by structures in the dorsolateral prefrontal cortex, anterior caudate nucleus, anterior cingulate, and medial temporal lobe, while learning in the reflexive, procedural-based learning system is mediated primarily by the posterior caudate nucleus and putamen (Ashby & Maddox, 2005; Ashby & O'Brien, 2005).

DUAL SYSTEM TASK MEDIATION

We study decision-making using two very different types of tasks. In *history-independent* situations the rewards available from the options in the environment are not affected by the history of previous choices—only the most recent selection. In these paradigms the rewards available for each option on each trial are set by the experimenter and vary based on the trial number. Many tasks used to study decision-making incorporate history-independent reward structures, including tasks like the Iowa Gambling task (e.g. Denburg, Tranel & Bechara, 2005), the Behavioral Investment Allocation Strategy task (e.g. Kuhnen and Knutson, 2005; Samanez-Larkin, Kuhnen, Yoo & Knutson, 2010), and the Monetary Incentive Delay task (e.g. Samanez-Larkin et al., 2007).

On the other hand, *history-dependent* tasks are tasks for which the rewards available from various options *depend* on the previous history of choices. This type of decision-making draws similarities to real world decision-making in that our decisions often affect what possibilities are available in the future. For example, one may choose to attend college or to seek employment. While this is only one decision, the choice affects the availability of future rewards at future decisions. If one chooses work over attending school then experienced-based positions (with associated rewards) become available. Alternately, if school is chosen then other rewards may be available. Similarly, one must often make the choice between spending money now and saving for later. Spending money now can provide an immediate reward, but saving for later can often result in a greater delayed reward. For these tasks in which immediate and long-term goals conflict, optimal performance is often not able to be achieved using simple reflexive strategies, but relies on reflective processing.

DEPRESSION

Depression is a common and recurrent condition. The World Health Organization has reported that over 120 million people currently suffer from depression, and many more have elevated depressive symptoms. In addition to predicting future suicide attempts, interpersonal problems, and substance abuse (Kessler et al., 2003; Kessler & Walters, 1998), depression is also known to affect a wide range of cognitive processes, spanning both reflexive and reflective domains.

Cognitive theories of depression (e.g., Beck, 1976; Teasdale, 1988) suggest that a contributing factor to depression is an attentional bias for depression-relevant themes. Depressed individuals focus attention on negative information (Mathews & MacLeod, 2005). Several studies have documented a negative attentional bias in depression (Mogg & Bradley, 2005), as well as an absence of a positive attentional bias (Ellis, Beevers, & Wells, 2011; Gotlib & Krasnoperova, 1998; Sears, Thomas, LeHuquet, & Johnson, 2010).

Decision-making is a complex process, but one critical aspect of decision-making is reward-based learning (i.e., Ridderinkhof & van den Wildenberg, 2004), which depends on the acquisition of knowledge, implicit or explicit, about the relationships between stimuli and actions (Berridge & Robinson, 2003). Thus, individuals must learn from available rewards and use this information to make decisions. We propose that some observed decision-making deficits associated with depression are due to negative attentional biases, which could undermine learning from rewards. That is, that hypersensitivity to punishment (Eshel & Roiser, 2010) and biased attention toward negative stimuli may cause suboptimal responding in reflexive decision-making tasks.

Depression is also associated with deficits in a range of reflective processes, such as problem solving (Elderkin-Thompson, Mintz, Haroon, Lavretsky, & Kumar, 2006), planning (Rogers et al., 2004), cognitive flexibility (Butters et al., 2004), and memory (Burt, Zembar, & Niederehe, 1995). We further hypothesize that impairments in these processes underlie the deficit associated with depression in reflective decision-making tasks (Blanco, Otto, Maddox, Beevers, & Love, 2013; Maddox et al., 2012).

THE PRESENT STUDIES

In the next chapter (Chapter 1) we explore the dependence of different types of decision-making tasks on explicit processing to establish that functioning necessary for one type of decision-making is not as critical for optimal performance in different types of decision-making. Importantly, this work suggests that improvements to processes necessary for improving reflexive processing may not be effective in improving other types of decision-making, such as reflective decision-making.

In Chapter 2 we explore the relationship between decision-making tasks and individual strategy predispositions. We do this to establish that we do not simply have "good decision makers" and "bad decision makers"—that individuals who perform well using one decision-making structure may not perform well in a different type of task. In Chapter 2 we also study the stability of strategy utilization over time to establish that, without intervention, individuals tend to rely on the same decision-making strategies regardless of their efficacy. As a whole, Chapters 1 and 2 seek to establish that the decision-making reward structures that we implement rely on different underlying processes, as outlined in the dual-systems hypothesis, and that improving decision-making performance will likely rely on different interventions that modify strategy engagement.

In the remaining chapters we explore targeted training techniques to improve both reflective and reflexive decision-making performance in individuals with elevated symptoms of depression. We hypothesize that although the same group of individuals may show deficits in multiple types of tasks, these deficits are likely due to different causes and thus should be approached using different modification strategies. In Chapter 3 we explore the effect of attention training to improve reflexive decision-making performance. We find that attention training is effective in improving reflexive decision-making, but is ineffective at improving reflective decision-making. Due to the influence of working memory on the history-dependent decision-making task, we attempt to improve decision-making using a working-memory training paradigm in Chapter 4. We find that working memory training using an operational span procedure is successful in improving subsequent history-dependent and history-independent decision-making performance.

The final chapter of this dissertation contains preliminary data from a long-term working memory training study. The goal of this endeavor is to produce longer-lasting changes in decision-making. The preliminary results of this study suggest that working memory training over a period of five weeks can change decision-making performance, with the greatest benefits observed in those who are trained with higher-difficulty, neutral stimuli.

Chapter 1: Dependence (and Independence) on Working Memory Resources

Decisions are an important part of daily life. While some decisions are isolated events, other decisions are more complicated, requiring the decision-maker to take into consideration the effect that each decision will have on available rewards in the future. In the current study we compare the effects of working memory load on these two different types of decision-making, using one task for which the available rewards on each trial do not depend on previous choices (history-independent), and another task in which the rewards available at each point depend on the participant's recent history of choices (history-dependent). Using the dual systems framework to form our hypotheses, we believe that working memory load will affect these two types of decision-making in different ways.

Dual learning systems theory suggests that there are at least two learning systems through which learning may be moderated: a *reflective* system that is available to conscious awareness and that uses working memory resources to develop and test hypotheses; and a *reflexive* system that is not available to conscious awareness and depends on learning via reinforcement (e.g. Ashby & Alfonso-Reese, 1998). Use of the reflective learning system requires participants to develop and test hypotheses, often relying on the use of verbal rules. Alternately, reinforcement-learning moderated by the reflexive system does not require the use of explicit processes. This dual-systems hypothesis has been supported in the domain of category learning through a combination of behavioral experiments and computational modeling evaluating the effect of working memory load on performance (Miles & Minda, 2011; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Specifically, a simultaneous working-memory task significantly reduces performance in category learning tasks that rely on explicit rule-based processing, but does not impair performance in category learning tasks relying on implicit procedural learning (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006).

We hypothesize that different types of decision-making tasks will be differentially affected by working memory load, similar to the results of the category-learning literature. Most decision-making tasks used in the laboratory, like the ones in the current study, can be classified as either history-independent or history-dependent. History-independent tasks are those for which the available rewards at each trial are only dependent on the current choice. In these tasks, the rewards available for each option are often pre-determined by the experimenter or selected randomly from a known distribution. The history-independent task that we use in the current study requires participants to repeatedly select between two reward options and learn which option gives the higher average reward via trial-and-error. In this task, the rewards given for each trial only depend on the option selected and the trial number. Alternately, experiments may require participants to determine the relationship between available rewards and their previous choice history, referred to as history-dependent decision-making, or state-based decision-making (i.e. Worthy, Cooper, Byrne, Gorlick & Maddox, 2014). The history-dependent task that we use in the current study also requires participants to repeatedly select between two reward options, but optimal performance depends on participants learning to forego the higher immediate reward to increase their long-term rewards.

The history-dependent task has been explicitly linked to working memory availability (Worthy, Otto, & Maddox, 2012). Participants who completed the decision-making task with a simultaneous working memory demanding dual-task selected the optimal choice less frequently than individuals in a single-task condition (Worthy et al., 2012), a finding that we seek to replicate. We hypothesize that the history-independent task is not similarly dependent on working memory resources and that performance can be successfully attained using automatic, reflexive processing (Cooper et al., 2014), but we have not directly evaluated this relationship using a similar dual-task experiment. In the present study we will examine the reliance of performance in these tasks on working memory using a dual-task procedure that has been used to examine the dependence of reflexive and reflective category learning on working memory (Zeithamova & Maddox, 2006), and used to examine the relationship between working-memory and history-dependent decision-making (Worthy et al., 2012). We expect that performance will be reduced in the dual task condition for the history-dependent task (replicating Worthy et al., 2012), but that performance will not be reduced in the history-independent task. The results of both tasks will be supplemented with computational modeling analyses that quantify the extent to which participants rely on heuristic-based strategies versus reinforcement learning strategies.

METHOD

Participants

Participants were 99 young adults recruited from the University of Texas at Austin. Participants were given course credit for their participation.

Decision-Making Tasks

Each participant completed 250 trials of the Martian Oxygen task (Figure 1.1) under single or dual task conditions. At the beginning of each trial the participant chose between two reward options, represented on the keyboard by button ‘Z’ and button ‘?/’. For each choice a positive reward was presented, which was then added to their cumulative reward total. After the cumulative total updated the next trial would begin and the participant would again be asked to choose between the two reward options. The participant was given the goal to maximize reward over the course of the experiment. The reward structure assigned to each task (unknown to the participant) determined the level of reward that the participant received for each selection on each trial.

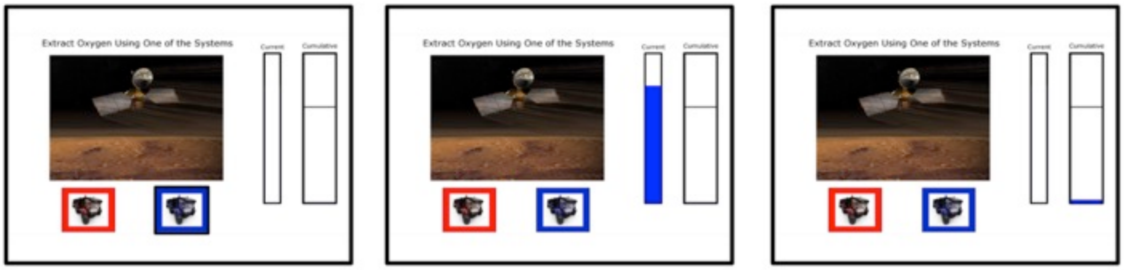

Figure 1.1: Sample Decision-Making Trial.
At the beginning of each trial, participants choose between two options. Participants are then shown the reward for that trial. The reward is added to their cumulative total and another trial begins.

The reward amounts given for each option were determined by the underlying reward structure: history-dependent or history-independent. In this history-dependent task, rewards available on each trial were dependent on the participants' recent history of choices. One of the options, the increasing option, caused the rewards available for both options to increase. The other option, the decreasing option, caused the future rewards available for each option to decrease. The precise reward given on each trial was calculated based on the number of increasing option selections in the 10 most recent selections. The increasing option is represented by h in the following equations:

The rewards given when the increasing option was selected:

$$30+5h;$$

While the rewards given when the decreasing option was selected:

$$40+5h$$

Thus, rewards received in this task were not independent and were determined by the participants' choice history. Repeatedly selecting the increasing option for 10 consecutive trials resulted in a reward of 80 points on each subsequent trial, while repeatedly selecting the decreasing option resulted in a reward of 40 points on each trial. The optimal strategy in this task was to repeatedly select the increasing option, which gave a smaller reward on each trial relative to the decreasing option, but caused the rewards for both options to increase in the long-term.

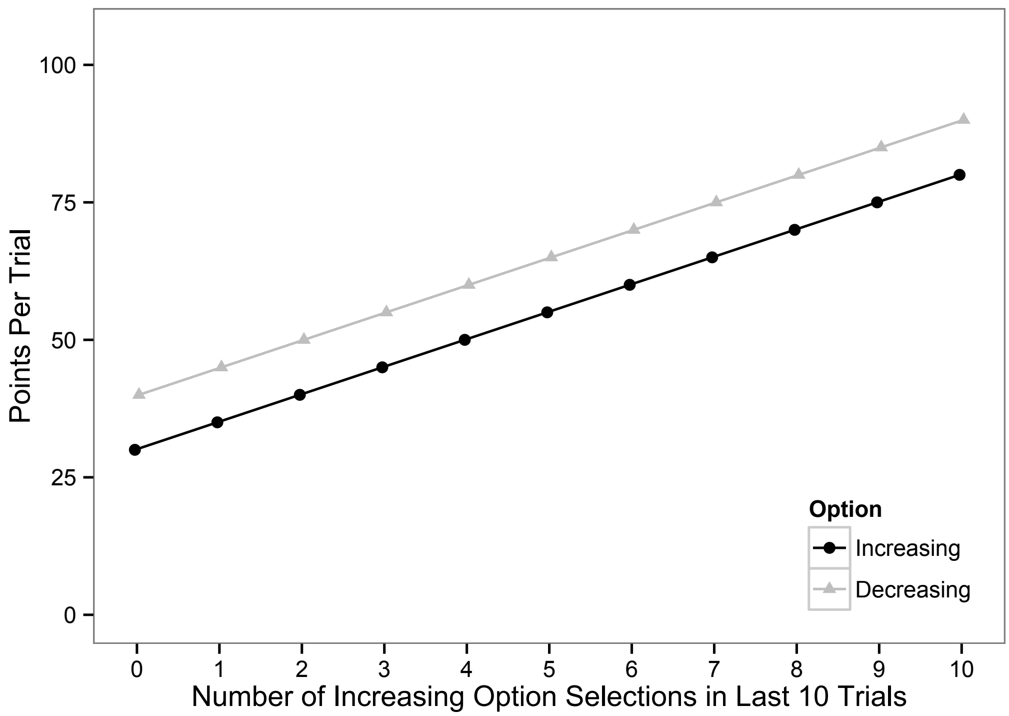

Figure 1.2: History-Dependent Reward Structure.
Rewards given for each option as function of the number of times the increasing option was selected over the previous ten trials. Selecting the increasing option ten consecutive times leads to a reward of 80 units of oxygen on each trial, whereas selecting the decreasing option ten consecutive times leads to a reward of 40 units of oxygen on each trial.

The rewards available on each trial in the history-independent task were only dependent on the trial number. One option gave an average reward of 55 points while the other gave an average reward of 65 points. Both had a standard deviation of 15 and were thus highly variable. The optimal strategy in this task was to exploit the option that gave highest average reward.

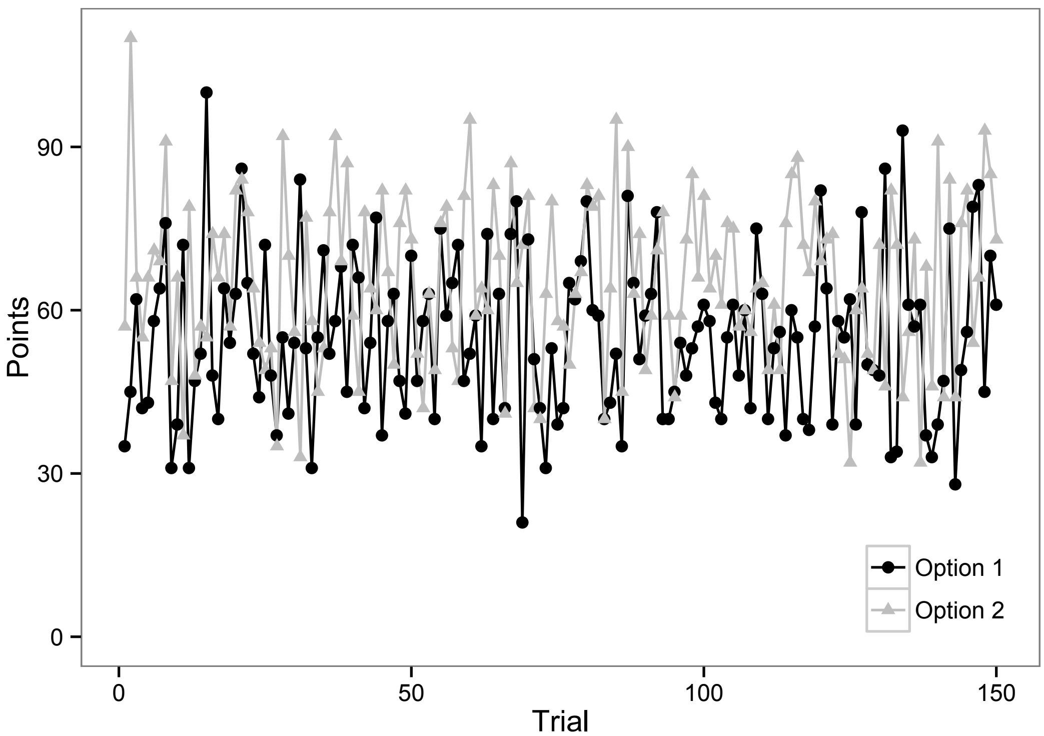

Figure 1.3: History-Independent Reward Structure.
Rewards are given for each option as a function of the trial number. Option A gives an average reward of 55, whereas option B gives an average reward of 65.

In the present study participants completed the history-dependent or history-independent decision-making task in either single or dual task conditions, a 2x2 design resulting in 4 conditions. In all conditions participants were given a goal of maximizing points. On each trial they repeatedly chose between two options, received a reward for the option that was selected, and had that reward added to their cumulative total.

Single vs Dual Task Conditions

Trials in the dual-task condition were separated by a working-memory demanding numerical analog of the Stroop Task (See Henik & Tzelgov, 1982; Stroop, 1935). Two numbers were displayed on either size of the screen that differed in numerical value and physical size. Participants were asked to remember which of two numbers was physically larger and which was larger in numerical value, and to hold that information in mind while deciding which reward option to select. At the beginning of the trial the two numbers for the concurrent task were presented on each side of the screen, one number on each side, for 200ms. After 200ms a uniform white mask covered the numbers for 200ms and participants were then allowed to make a decision and given feedback regarding their choice. A new screen then appeared that prompted participants with either “VALUE” or “SIZE,” and participants indicated which side had the number largest in either numerical value or physical size. After they made their response they were told whether they were correct or not, and the next trial began. Participants in the single-task condition completed only the decision-making task with an inter-trial interval designed to match the timing of the dual-task condition.

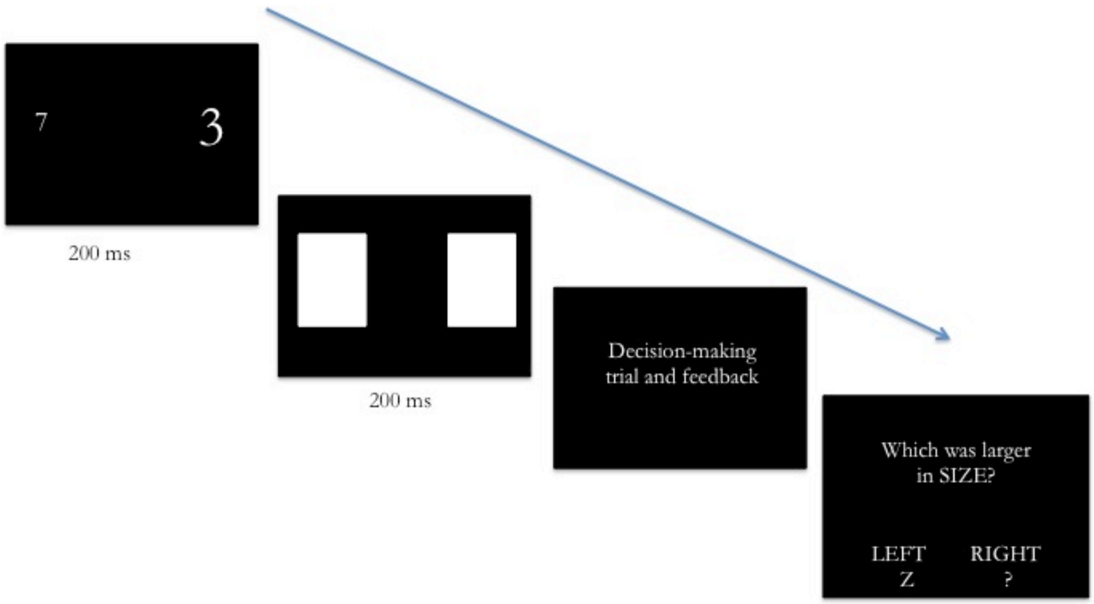

Figure 1.4: Dual-Task Trial Details.
Participants are shown two numbers on either side of the screen that vary in physical size and value. Participants have to hold this information in working memory during the decision-making trial and feedback, after which they are asked which side was bigger in either value or physical size.

In category learning, this dual task significantly reduces performance in reflective tasks that rely on explicit rule-based processing, but does not impair performance in reflexive procedural tasks (Zeithamova & Maddox, 2006). We expect that performance will be reduced in the dual task condition for the history-dependent task (replicating Worthy et al., 2012), but will not be significantly reduced in the history-independent task.

Results

Performance on these tasks is measured by the proportion of trials in which participants select the optimal choice (Figure 1.5). Using a 2x2 ANOVA, we find an interaction, $F(1,95) = 3.527$, $p = .063$, partial-$\eta^2 = .036$. We also find a main effect of both reward structure, $F(1,95) = 26.139$, $p < .001$, partial-$\eta^2 = .216$, and dual task condition, $F(1,95) = 9.767$, $p = .002$, partial-$\eta^2 = .093$. Using pairwise comparisons to decompose the interaction, the effect of dual task in the history-dependent condition was highly significant: $t(53) = 3.501$, $p = .001$, Cohen's $d = .962$; while the effect of dual task on history-independent decision-making was not significant, $t(42) = .927$, $p = .359$, Cohen's $d = .286$. This indicates that history-dependent decision-making performance was negatively affected by the simultaneous dual task procedure, while history-independent decision-making performance was not affected by the working-memory taxing dual task.

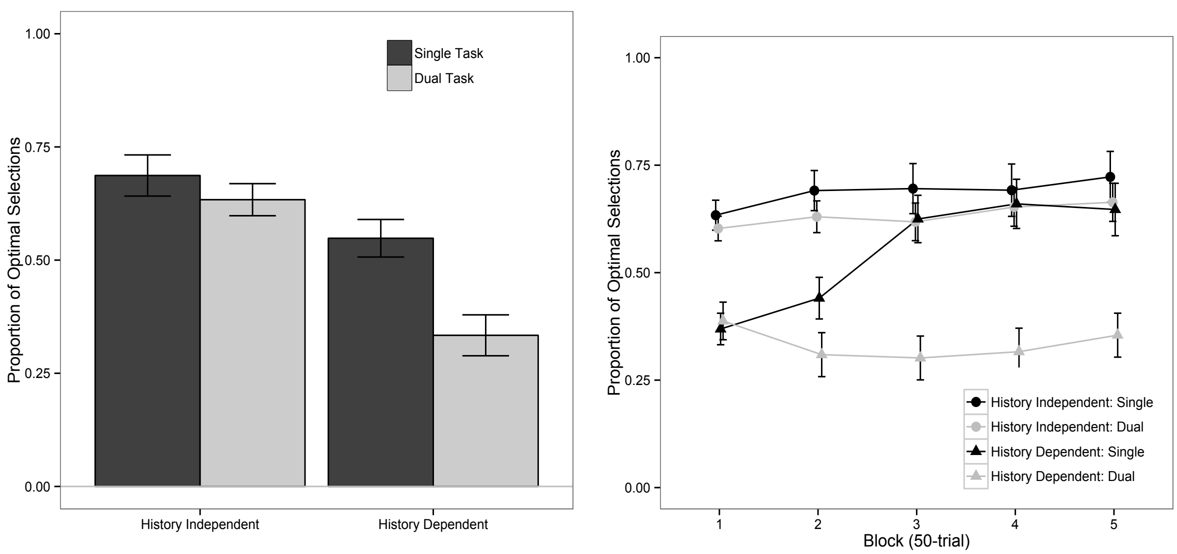

Figure 1.5: Chapter 1 Performance.
Performance is measured by proportion of optimal selections. On the left, performance is averaged across all 250 trials. On the right, performance is broken into five blocks of 50 trials to show changes in learning across the course of the experiment. Error bars represent standard error of the mean.

We also examined learning across the task by partitioning performance across the 250-trial experiment into five blocks of 50 trials. We observed a significant block x reward structure x dual task interaction, $F(4,92) = 2.917$, $p = .025$, partial-$\eta^2 = .113$. Within the history-independent task performance increased from the first block ($M = .62$) to the last block ($M = .69$), $F(4, 168) = 2.195$, $p = .072$, partial-$\eta^2 = .050$. However, block did not interact with condition, ($p = .910$), indicating that performance changed at similar rates between the two conditions. The main effect of condition was also not significant ($p = .359$), indicating that the dual-task condition did not negatively impact performance in the history-independent decision-making task. In the history-dependent task, we found that performance improved from the first block ($M = .38$) to the last block ($M = .51$), $F(4, 212) = 7.314$, $p < .001$, partial-$\eta^2 = .121$. Block also interacted with condition, $F(4, 212) = 12.038$, $p < .001$, partial-$\eta^2 = .185$. Performance in the first block was similar between single-task ($M = .37$) and dual-task ($M = .39$) conditions, but performance in the single-task condition improved by the last block ($M = .65$) while performance in the dual-task condition did not ($M = .35$). The main effect of condition was also significant, $F(1, 53) = 12.258$, $p < .001$, partial-$\eta^2 = .188$, indicating that participants performed better in the single-task condition ($M = .55$) than in the dual-task condition ($M = .34$).

Modeling

One advantage of our approach is that the decision-making tasks are amenable to computational modeling that can provide additional insight into the decision-making behavior of our participants. The proportion of optimal sections (reported above) is useful in assessing performance, but does not provide insight into the strategies that participants implement. Modeling is especially useful when similar performance can be attained through different approaches. We applied a series of computational models to the individual participants' data on a trial-by-trial basis. The models included a heuristic-based win-stay-lose-shift (WSLS) model and a Reinforcement Learning (RL) model.

WSLS models have been used to model behavior in decision-making tasks (Otto, Taylor & Markman, 2011; Steyvers, Lee, & Wagenmakers, 2009; Worthy et al., 2012; Worthy & Maddox, 2011). The WSLS model assumes that participants compare the reward received on the present trial to the reward that they received on the previous trial and has a total of two free parameters $P(stay|win)$ and $P(shift|loss)$. If the reward is greater than or equal to the reward on the previous trial it is a "win" trial and participants "stay" by picking the same option on the next trial with an estimated probability.

$$P\,(a_i\,,\,t\,|\mathrm{choice}_{t-1} = a_i \,\&\, r(t-1) \geq r(t-2)) = P(\mathrm{stay}|\mathrm{win}) \qquad (1.1)$$

The probability of switching to the other option after a "win" is 1- $P(stay|win)$. If the reward is less than the reward received on the previous trial it is a "loss" trial, and participants "shift" by picking the other option on the next trial, with an estimated probability.

$$P\,(a_j\,,\,t\,|\mathrm{choice}_{t-1} = a_i \,\&\, r(t-1) < r(t-2)) = P(\mathrm{shift}|\mathrm{loss}) \qquad (1.2)$$

The probability of staying with an option after a "loss" is 1-$P(shift|loss)$. Utilization of a WSLS strategy can lead to good performance in the history-dependent task since performance relies on one's ability to observe how rewards improve or decline across trials (Worthy et al., 2012).

The Softmax RL model accounts for decision-making behavior by updating expected reward values (EVs) for each option, i, on each trial, t, in Equation 1.4. Expected values (EVs) are initialized at zero for each option and are updated based on prediction error δ:

$$\delta = r(t) - EV_{i,t} \qquad (1.3)$$

Here $r(t)$ is the reward received for the chosen option. Prediction errors are used to update expected values each time an option is chosen based on the update rule:

$$EV_{i,t+1} = EV_{i,t} + \alpha \cdot \delta \qquad (1.4)$$

The recency parameter (α) weighs the degree to which participants use their most recently received reward to update expected values. As α approaches 1, recent rewards are given greater weight, while an α of zero indicates that no learning took place. The expected values for each option are used to determine the probabilities for selecting each option by the Softmax decision rule (Sutton & Barto, 1998):

$$P(a_i, t) = \frac{e^{[\theta \cdot EV(a_i, t)]}}{\sum_{j=1}^{2} e^{[\theta \cdot EV(a_j, t)]}} \quad (1.5)$$

Where θ is an inverse temperature parameter representing the degree to which the option with the highest EV is chosen. Higher values of θ indicate that the highest valued option is chosen more often.

We fit the computational models described above to each participant's data on a trial-by-trial basis to obtain the fit of each model minimizing negative log-likelihood. To analyze an individual participant's reliance on one model over the other, and consistent with Worthy et al. (2012), we subtracted the fit of the WSLS model from the fit of the RL model. Because lower fit values indicate better model fit, positive values of the WSLS difference metric can be interpreted as the WSLS model being the better fitting model, while negative values indicate that the RL model is the better fitting model.

We conducted a 2 (reward structure) x 2 (dual task) ANOVA on the WSLS difference metric for each group. We observed a main effect of dual task condition $F(1,95) = 19.276$, $p < .001$, partial-$\eta^2 = .169$. Main effects of reward structure and reward structure by dual task interaction were both non-significant, $p > .2$. In both the history-independent and history-dependent conditions participants were best fit by the WSLS model when working memory was not taxed (M = 9.62, M = 13.15). Both groups were better fit by the reinforcement-learning model when working memory was taxed with a concurrent dual task (M = -10.70, M = -4.31).

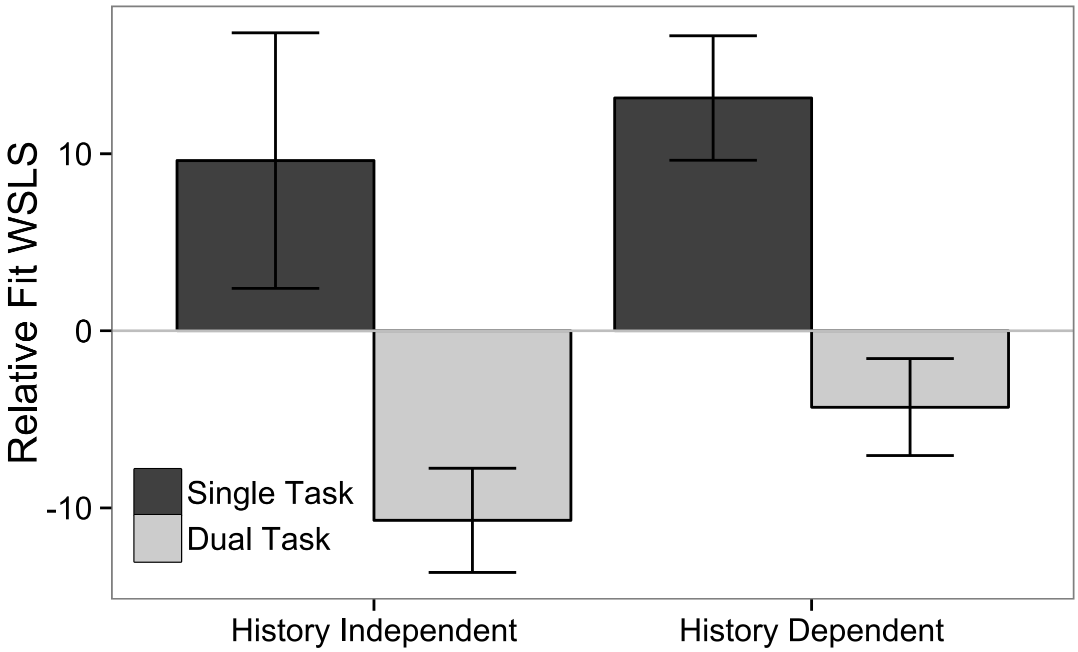

Figure 1.6: Chapter 1 Modeling Results.
This graph shows the difference between the fit of the WSLS and the RL model, calculated for each participant and averaged within the group. Higher values indicate better relative fit of the WSLS model. Error bars represent standard error of the mean.

DISCUSSION

These results indicate that participants rely on more heuristic-based strategies when working memory is not taxed. However, when working memory is taxed by a concurrent dual task, participants shift to more implicit strategies that are captured by the reinforcement-learning model.

For the task that relies heavily on reflective processing for good performance, the history-dependent task, shifting to a reflexive strategy significantly impairs performance.

However, in the history-independent task performance does not decline with a shift to reflexive reinforcement-learning strategies. This is because good performance on the history-independent task can be achieved using reflexive strategies. Importantly, these results show that performance on the history-dependent task is dependent on the availability of working memory resources, while performance on the history-independent task is not dependent on working memory.

The findings of this study indicate that two types of decision-making tasks used in these studies, (history-dependent and history-independent) rely on different underlying mechanisms for optimal performance. Performance in the history-dependent task relies on the use of working memory resources, while performance in the history-independent task is not dependent on working memory. Training methods that improve reflexive processing or encourage the use of reflexive strategies, even if effective at improving history-independent performance, will likely not generalize to the history-dependent task.

Chapter 2: Stability of Decision-Making Performance and Strategy Engagement

In Chapter 1 we established that performance in reflective (history-dependent) decision-making is dependent on working memory, while performance in reflexive (history-independent) decision-making is not dependent on working memory—that good performance in the history-independent task can be attained even under working memory load and with the use of implicit reinforcement-learning strategies. In the current chapter we explore individual biases toward these reflective and reflexive strategies. If decision-making performance and strategy engagement are stable, then interventions that seek to change decision-making performance should seek to change the strategies that are being implemented. Combined with Chapter 1, the current chapter will be useful in designing interventions to modify decision-making in the following chapters.

Optimal performance in most decision-making tasks relies on the use of either *reflective* or *reflexive* decision-making strategies. To date, reflective vs. reflexive system-level competition has not been fully explored in decision-making. Both history-dependent and history-independent tasks have been widely used to study decision-making performance in a number of different populations, including older and younger adults (Worthy et al., 2011) and individuals with symptoms of depression (Beevers et al., 2013, Maddox et al., 2012). Additional work in our labs has looked at the effect of personality traits and situational factors on performance in these tasks (e.g. Cooper et al., 2014). A number of our studies have used computational modeling to compare strategy implementation between groups or conditions. One gap in our rigorous line of research is a within-subjects comparison of these types of decision-making reward structures. In the current study we evaluate predispositions to decision-making strategies by fitting computational models to within-subjects history-dependent and history-independent decision-making data. This line of research will address several key questions. In Experiment 1 we test whether individual performance in one reward structure is indicative of performance in other reward structures, and whether individuals rely on the same or different strategies in each type of experiment. In Experiment 2 we investigate whether or not the engagement of strategies is consistent over time.

EXPERIMENT 1: WITHIN-SUBJECT DECISION-MAKING PERFORMANCE

In Experiment 1 we collect within-subject decision-making data using the history-independent and history-dependent decision-making tasks to evaluate the relationship between these tasks. One possibility is that individuals who perform well in one type of task will perform well in other types of tasks—leading to positive correlations in performance but negative correlations in model fit.

An alternate possibility is that individuals who excel in reflective decision-making tasks will perform poorly in the reflexive decision-making task. We predict that performance between tasks will be correlated due to the reliance on the same strategies. We make these predictions because, through the use of reflective strategies, optimal performance in the history-dependent task requires participants to forego the higher immediate reward on each trial in order to maximize long-term rewards. For the history-independent task optimal performance is achieved by selecting the higher immediate reward. Thus, individuals who have a stronger preference for the immediately rewarding option, supported by the use of reflexive strategies, should do better in the history-independent tasks while individuals who show a greater preference for long-term rewards and reflective strategies should do better in the history-dependent task.

Computational modeling provides insight into the specific learning operations (e.g. reflective vs. reflexive) that participants employ (Cleeremans & Dienes, 2008) and can be used to gain additional information about individual variability in task performance. In short, information about overall task performance, or proportion of optimal selections, provides information about the level of performance but does not necessarily tell us much about the specific strategy being used by a participant because some reflexive and reflective strategies can yield similar rates of performance. In order to gain additional information about participants' reliance on reflective and reflexive strategies we will utilize computational modeling. We expect that individual participants will tend to rely on the same strategies, even when the strategies are not optimal for the particular type of task. We also expect that these strategy biases will (at least partially) account for observed differences in performance between different types of tasks.

EXPERIMENT 1 METHOD

Participants

Participants were young adults (M_{age} = 19.07; SD_{age} = 1.31) recruited from the University of Texas at Austin. Each participant (N = 38) completed decision-making tasks with both history-independent and history-dependent reward structures[1]. The order in which they received the different reward structures was counterbalanced across participants. For each participant, each task (reward structure) was paired with one of three surface features. Participants were compensated $10 per hour for their participation.

For each task participants completed 250 trials. At the beginning of each trial the participant chose between two reward options, represented on the keyboard by button 'Z' and button '?/'. For each choice a positive reward was presented, which was then added

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[1] Participants also completed a decreasing-optimal decision-making task, which was not included in this dissertation.

to their cumulative reward total. After the cumulative total updated the next trial would begin and the participant would again be asked to choose between the two reward options. Regardless of surface feature, in each task participants were always given a goal to maximize their amount of cumulative reward across the course of the experiment.

Reward Structures

The reward amounts given for each option were determined by the underlying reward structure: history-dependent and history-independent. In the history-dependent task, rewards available on each trial are dependent on the participants' recent history of choices. One of the options, the increasing option, causes the rewards available for both options to increase. The other option, the decreasing option, causes the future rewards available for each option to decrease. The precise reward given on each trial is calculated based on the number of increasing option selections in the 10 most recent selections. The increasing option is represented by h in the following equations:

The rewards given when the increasing option was selected:

$$15+5h;$$

While the rewards given when the decreasing option was selected:

$$55+5h$$

Thus, rewards received in this task were not independent and were determined by the participants' choice history. Repeatedly selecting the increasing option for 10 consecutive trials resulted in a reward of 65 points on each subsequent trial, while repeatedly selecting the decreasing option resulted in a reward of 55 points on each trial. The optimal strategy in this task was to repeatedly select the increasing option, which gave a smaller reward on each trial relative to the decreasing option, but caused the rewards for both options to increase in the long-term.

Unlike the history-dependent task, the rewards available on each trial in the history-independent task are not based on the participants' recent pattern of choices, but only on the most recent selection. One option gave an average reward of 55 points, while the other option gave an average reward of 65 points. The standard deviation of each option was 10 points. Thus, while an option may give a higher average value, it will not give a higher value on every trial.

Results

The proportion of trials on which participants selected the optimal choice was used to assess performance in each task. For the history-independent task, the optimal choice was the option that awarded an average of 65 points, while the sub-optimal choice was the option that gave an average reward of 55 points. In the history-dependent condition the optimal choice was the increasing option, the option that gave the lower reward on each trial but caused the rewards available for both options to increase.

Performance correlations were observed between the tasks. The proportion of optimal selections in the history-dependent task was negatively correlated with proportion of optimal selections in the history-independent task $r(37) = -.285$, $p = .083$, though marginally significant.

Modeling

The data from each condition were fit with the Reinforcement Learning and WSLS models as described in Chapter 1. We compared the negative log likelihood values of these two models by subtracting the fit of the Win-Stay Lose-Shift model from the fit of the Reinforcement Learning model. Positive values of the WSLS difference metric indicate that the WSLS model was a better fit for the participant, while negative values indicate that the RL model was the better fit for the participant.

We first checked to see if relative reliance on the WSLS model was correlated with performance in either task. Previous work suggests that reliance on simple heuristic-based strategies implemented in the WSLS model relative to RL strategies correlates to better performance in the history-dependent task, but correlates to worse performance in a similar history-independent task (Worthy & Maddox, 2011). In our study we observe similar effects: higher relative fit of the WSLS model was positively correlated with performance in the history-dependent task, $r(37) = .543$, $p < .001$, but negatively correlated with performance in the history-independent task, $r(37) = -.468$, $p = .003$.

We also examined individual participants propensity to engage the same strategies by analyzing the correlation between relative fit of the WSLS model in the history-dependent and history-independent conditions, $r(37) = .666$, $p < .001$, indicating that individuals with high relative fit of the WSLS model in the history-dependent condition tended to be better fit by the same model in the history-independent condition. This trend was statistically significant regardless of the task that participants completed first (ps < .05). In addition, order in which the tasks were presented did not have a significant effect on performance or relative model fit in either task (ps > .330).

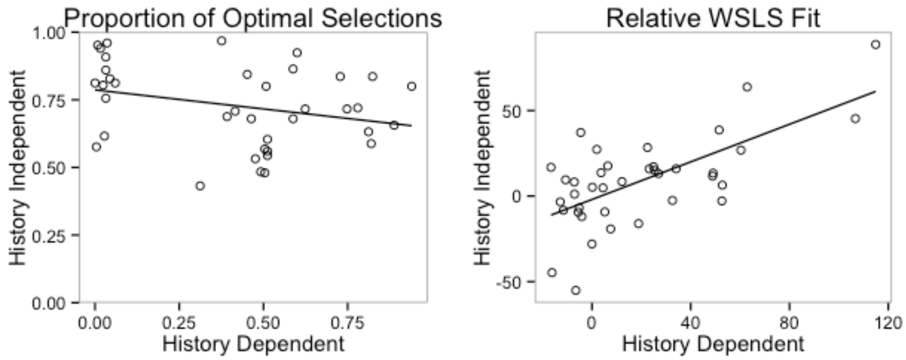

Figure 2.1: Chapter 2 Experiment 1 Results.
Left: Correlation between performance in the history-dependent and history-independent tasks. Performance is defined as the proportion of trials on which the optimal choice was selected. Right: Correlation between the relative fit of the WSLS model in the two tasks. The relative WSLS metric represents the difference in fit between the WSLS and RL model, with higher values indicating better fit of the WSLS model.

In addition to comparing the relative model fit estimated across all 250 trials, we also fit each model to each 50-trial block to determine whether the best-fitting model changed across the course of the experiment, and whether participants engaged similar strategies early or late in the experiment.

In the history-dependent task, the proportion of participants who were best fit by the WSLS model was stable across the course of the experiment (Figure 2.2). In the history-independent task, the proportion of participants best fit by the WSLS model decreased from 66% in the first block to 37% in the last block. This shift is consistent with previous work (e.g. Paul & Ashby, 2015) that suggests that participants in tasks that rely on implicit processing may begin with reflective, rule-based strategies before shifting to implicit, reflexive strategies. Relative model fit was strongly correlated between tasks in block 1 $r(37) = .485$, $p = .002$ and dissipated by block 2, ($p = .607$).

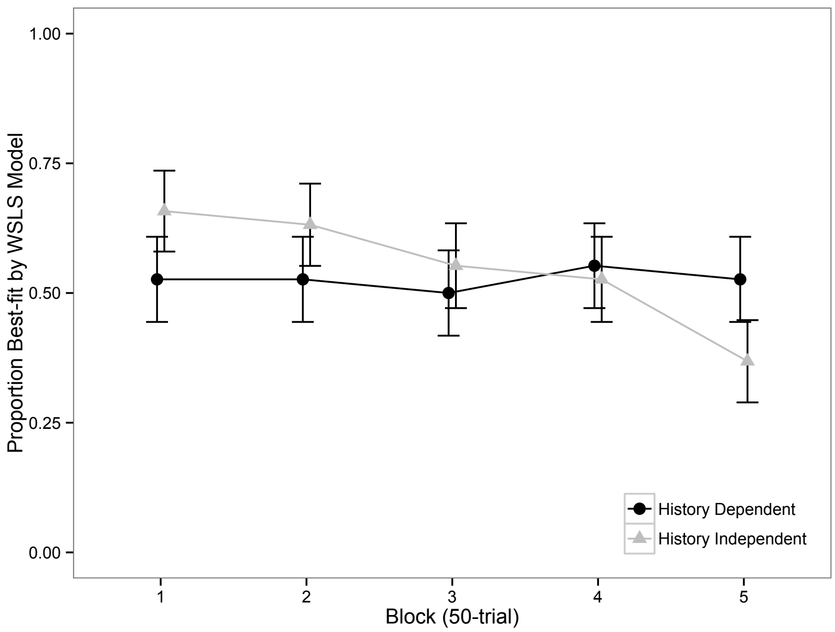

Figure 2.2: Relative Model Fit By Block.
Proportion of participants that were best fit by the Win-Stay Lose-Shift model, relative to the Reinforcement Learning model, at each 50-trial block.

We evaluated the generalizability of the WSLS and RL models across tasks using the *generalization criterion* (Busemeyer & Wang, 2000). Similar to Yechiam & Busemeyer (2008) and Ahn, Busemeyer, Wagenmakers, & Stout (2008) we utilize the within-subjects design to apply the generalization criterion at an individual level by fitting each model to each participant's first task and using their parameter estimates to make a prediction for each person for the second task.

Each model is compared to a baseline model by computing the G^2 metric, the difference in log-likelihood between the test model and a baseline model that assumes equal probabilities of selecting each option. Positive values of G^2 imply that the model can make better predictions than the baseline model. For each model, we calculate the average G^2 value as well as the proportion of participants for which the G^2 metric is greater than zero. A proportion greater than .5 indicates that the model is a better fit than the baseline model for more than 50% of participants.

$$G^2 = 2 \bullet [LL_{model} - LL_{baseline}]$$

The generalization criterion results are presented in Table 2.1. These results show that the WSLS model performed better than the RL model for predictions of history-dependent performance using history-independent parameters, as well as history-independent performance using history-dependent parameters. The RL model only performed better than chance in predicting the history-independent task.

These results also indicate that generalization from the history-dependent task to the history-independent task was better than from the history-independent task to the history-dependent task. These results are consistent with previous results (e.g. Ahn et al., 2008), which speculated that predictions using the generalizability criterion are better when the parameters are estimated using tasks that have less payoff variability. Thus, predictions using the history-independent task may be lower than those using the history-dependent task because the rewards given on each trial have a relatively high standard deviation.

Table 2.1: Generalization criterion.

		G^2 Index	Proportion Positive
Predicted History-Dependent	RL	-28.29	0.50
	WSLS	150.83	0.90
Predicted History-Independent	RL	-72.77	0.61
	WSLS	103.55	0.94

Experiment 1 Discussion

In this study we evaluated the relationship between individuals' performance in a history-dependent task for which available rewards depended on their previous history of choices, and a history-independent task for which available rewards were drawn from a normal distribution. Previous research suggests that the history-dependent task is optimally approached using simple heuristic based strategies, captured by the Win-Stay Lose-Shift model, while history-independent decision-making is optimally approached using more automatic, reflexive processes captured by reinforcement learning models (Worthy & Maddox, 2011). This work utilized a within-subjects approach to determine whether individuals showed biases toward one strategy over another, regardless of the optimal task strategy.

Our findings indicate that performance is correlated across tasks. Individuals who perform well in the history-dependent task perform poorly on the history-independent task, though with a somewhat weak correlation. Perhaps surprisingly, stronger correlations were observed in the relative fit of computational models (relative WSLS fit), indicating that individuals were engaging the same types of strategies regardless of the type of task.

In Experiment 2, we will determine whether or not individuals rely on the same strategies across time. If individuals do rely on the same strategies over time, then interventions that seek to change performance will benefit from the use of computational modeling to determine whether or not the intervention successfully modifies strategy engagement.

Experiment 2: Stability of Decision-Making Strategies across Time

The findings of Experiment 1 lead us to believe that individuals are biased toward decision-making strategies independent of the type of decision-making task in which they are engaged. A second question that we would like to answer is whether or not the reliance on specific strategies persists over time. One possibility is that individuals who rely on a given strategy will continue to rely on the same strategy, even after several hours or days have passed. The other possibility is that reliance on different strategies is more random and varies based on a number of potential factors, such as mood, time of day, energy, etc.

The stability of decision-making strategy reliance (at baseline) is particularly important when considering long-term training studies. In later chapters we strive to change decision-making behavior using single-session techniques and long-term training. Two key assumptions in these training studies are that individuals have a natural bias toward certain decision-making strategies, and that these strategies, without intervention, are relatively stable. The following study tests the assumption that decision-making strategies are stable by administering the same decision-making task to individuals separated by one week and assessing their relative reliance on WSLS and RL strategies.

EXPERIMENT 2 METHOD

Participants

University of Texas undergraduate students (N = 36) were recruited from the University and received research credit for the Introduction to Psychology course.

Procedure

Participants were told that they were signing up for a two-part study. In the first session participants completed a decision-making task with either martian oxygen or house painting surface features. Six-to-eight days later participants completed their second session, which consisted of the decision-making task with the alternate surface feature. Participants were not told that it was the same decision-making task.

Each participant was randomly assigned to the history-dependent (n = 17) or the history-independent task (n = 19). The reward structure was consistent between the two sessions. The reward structures in this experiment were identical to the reward structures used in Chapter 1.

RESULTS

Performance in each task was measured using the proportion of optimal selections. For the history dependent task, this was the option that provided the lower immediate reward but caused the rewards available for both options to increase. For the history-independent task the optimal selection was the option that provided the higher average reward, 65 points. First we evaluated the relationship between decision-making performances across the span of one week.

In the history-dependent task, performance was correlated over the span of one week, $r(16) = .538$, $p = .026$. However, relative model fit (as calculated in Chapter 1), showed a stronger correlation between the two sessions, $r(16) = .641$, $p = .006$, indicating that relative fit of WSLS or RL strategies was correlated across time.

For the history-independent task, performance on the first session was correlated with performance in the second session, $r(18) = .459$, $p = .048$. Relative model fit was also correlated, though marginally significant, between the first and second session of the history-independent task, $r(18) = .413$, $p = .079$.

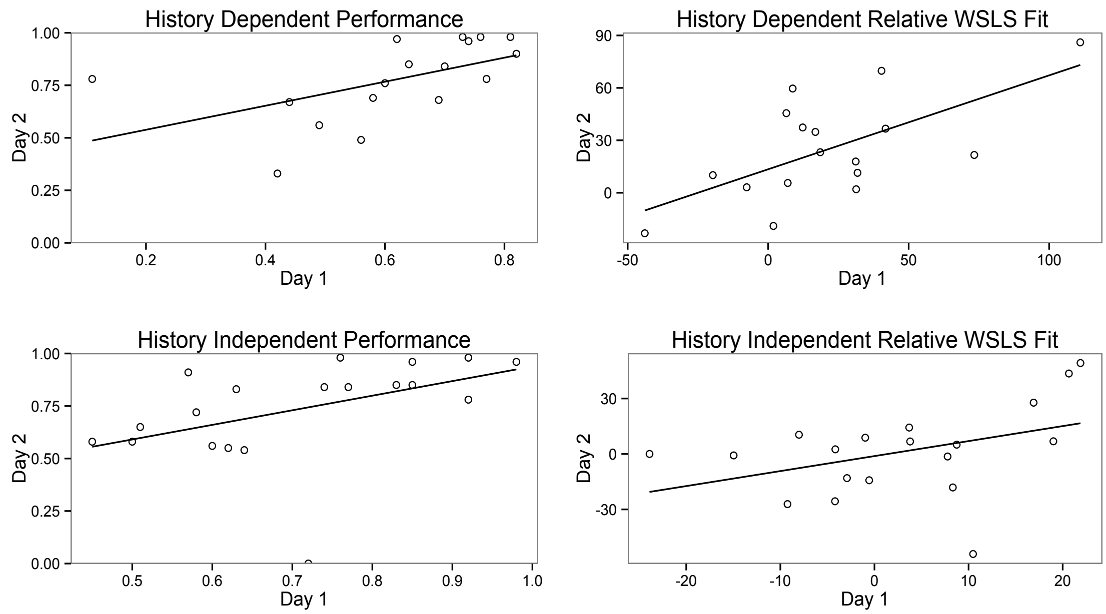

Figure 2.3: Chapter 2 Experiment 2 Results.
Top Left: Correlation between day 1 and day 2 performance in the history-dependent task. Top Right: Correlation between relative model fit (relative WSLS fit) on day 1 and day 2 for the history-dependent task. Bottom Left: Correlation between day 1 and day 2 performance in the history-independent task. Bottom Right: Correlation between relative model fit (relative WSLS fit) on day 1 and day 2 for the history-independent task.

EXPERIMENT 2 DISCUSSION

The results of Experiment 2 indicate that decision-making is relatively stable over a period of one week. For both the history-dependent decision-making task and the history-independent decision-making task, individuals performed similarly during their first session and their second session. Importantly, the relative model fits were also correlated across time. This indicates that individuals not only performed similarly in the task across time, but also relied on the same strategies across time.

The stability of decision-making strategies across time is particularly important when considering strategies for modifying decision-making behavior. This study indicates that without intervention decision-making performance and strategies are both relatively stable. If decision-making performance is to be modified, studies should seek to change the strategies that are being utilized by participants.

Chapter 2 General Discussion

The findings of Experiment 1 indicate that individuals are biased toward decision-making strategies regardless of the optimal strategy for the type of task. This indicates that group differences observed in decision-making studies, such as differences between age groups and other individual differences, might be attributable to reliance on different strategies—in particular a bias toward strategies that are sub-optimal to the type of task that is being tested. Importantly, future studies that identify a group decision-making deficit should examine performance in other types of decision-making—if a group deficit is attributable to engagement of a competing system, the group may actually show an advantage in alternate task types. This is already evident in current work where older adults show deficits in history-independent decision-making, but advantages in history-dependent decision-making (Worthy et al., 2011).

This work also has implications for training studies. If groups show deficits in certain types of decision-making, approaches at modifying decision-making performance may focus on trying to shift engagement from reflective strategies to reflexive strategies (or vice-versa). Additionally, the findings of Experiment 2 indicate that these biases in reliance on particular decision-making strategies, captured by computational models, persist over time. The stability of decision-making strategies without intervention is an important consideration for future studies that seek to change decision-making performance. Specifically, participants did not shift from one strategy to another simply because they were exposed to the reward structure multiple times, and performance was relatively stable. Future studies that seek to change decision-making performance with long-term training would benefit from pre and post measurements using the same decision-making task so that changes in model fits can be assessed.

Chapter 3: Depression, Attention, and Decision-Making

One group with known deficits in both history-dependent and history-independent decision-making is individuals with elevated symptoms of depression (e.g. Beevers et al., 2013; Maddox et al., 2012). We hypothesize that these deficits are due to different underlying causes. Depression is associated with declines in working memory, planning, and problem solving. These reflective processing deficits are hypothesized to underlie the history-dependent decision-making deficit. Depression is also associated with attenuated implicit reward sensitivity and biased attention to negative information. These reflexive processing deficits are hypothesized to underlie the history-independent decision-making deficit. Thus, increasing the engagement of working memory processes should improve history-dependent decision-making, while modifying implicit attention to positive and/or negative stimuli should improve history-independent decision-making. We test this by exploring the effects of attention training in Chapter 3 and working memory training in Chapter 4.

EXPERIMENT 1: ATTENTION TRAINING AND HISTORY-INDEPENDENT DECISION-MAKING (COOPER, GORLICK, WORTHY, BEEVERS & MADDOX, 2014)

Recent research suggests that biases in attention toward negative stimuli can be altered with targeted training. MacLeod and colleagues (2002) showed that attention training could create a negative bias in healthy individuals. Similarly, Wadlinger and Isaacowitz (2008) found that healthy individuals trained to direct attention toward positive stimuli spent less time viewing negative images, demonstrating a learned aversion to negative stimuli. This work suggests that attention training may have potential therapeutic value (Hakamata et al., 2010; Hallion & Ruscio, 2011). Building upon this work, Wells and Beevers (2010) used a variant of the dot-probe task (MacLeod, Mathews, & Tata, 1986) to train depressed individuals to shift attention away from negative images. Depressed individuals in the active attention training condition showed a reduced bias toward negative items and reported significant reductions in depressive symptoms two weeks post-training compared to control participants.

In the present research we use a variant of Wells and Beevers' attention training paradigm to direct attention toward positive information in order to improve reward-based decision-making. During training, participants viewed positive and neutral word pairs followed by a dot probe. In the active attention training condition, positive words predicted the probe location 85% of the time, whereas in the placebo training condition, neither word type (neutral or positive) predicted the probe location. Thus, the training paradigm implicitly trained participants to shift their attention toward positive information.

Following training, participants completed a decision-making task similar to that used in Beevers et al. (2013). One concern about the task used in Beevers et al. was that the reward values for each option were too dramatically different, making the task too easy and subsequently diminishing performance differences associated with depression. Thus, the present study increased the variability of each option. This increased variability in the reward structure makes the task more challenging by requiring participants to learn the value of each option by taking rewards over several trials into consideration, as opposed to responding only to the most recently received reward. This is important because previous research suggests that depressed individuals are impaired at integrating reward history over time (Pizzagalli et al., 2008). Supporting this idea, our prior work (Beevers et al., 2013) found that depressed individuals were more likely to alter their expected values for each option based on *recently* received rewards, whereas non-depressed control participants relied on a longer sequence of previous rewards in determining expected reward value.

Taken together, we make the following predictions. First, we predict that individuals with elevated depressive symptoms who receive placebo attention training will show a decision-making performance deficit relative to those without depressive symptoms. Second, we predict that individuals with elevated depressive symptoms who receive active attention training toward positive stimuli will show enhanced performance compared to those in the placebo training condition.

METHOD

Participants

Participants were seventy-five undergraduate students who completed the study as a part of a research requirement for an introduction to psychology course. Participants completed the short form of the Beck Depression Inventory (BDI; Beck & Steer, 1993) during a pre-testing survey battery. Participants whose scores were above 7 on the short form of the BDI-SF were contacted about participating in the high CES-D groups, while participants whose scores were below 7 on the short form were contacted about participating in the low CES-D control group.

Table 3.1: Chapter 3 Experiment 1 demographic characteristics

	Low CES-D	*High CES-D*	
	No Training	Placebo Training	Active Training
Sample size	33	22	20
CES-D: mean (sd)	6.58 (3.21)	26.95 (5.94)	28.9 (6.71)

**Standard deviations in parentheses.*

Procedure

At the beginning of the experimental session all participants completed a demographic form and a series of computer-based questionnaires that included the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977). The CES-D scores were used to verify that participants were still experiencing depressive symptoms at the time of testing and to validate previously recorded BDI scores. Participants with elevated levels of self-reported depressive symptoms were randomly assigned to the attention training or placebo training groups. Participants were not told that depression was a measure of interest and were not told anything about their group membership. It is also important to note that the term "training" was not mentioned to the participants until they were debriefed at the end of the experiment. This ensured that the participants were unaware of the study's purpose as well as experimental condition.

For the placebo training and active training groups, participants completed three blocks (all in the same session) of the attention-training task, approximately fifteen minutes each. Each block consisted of 168 trials for a total of 504 trials. Before and after training participants completed a two-item questionnaire about their current mood. Participants were given two minutes between each block to relax before starting the next block. Immediately following training, participants completed the decision-making task. The low CES-D group completed the decision-making task immediately following completion of demographic information and questionnaires.

Following convention (Weissman & Sholomskas, 1977), participants who scored 15 or less on the CES-D were classified as having low depressive symptoms, and participants who obtained a 16 or greater were classified as having elevated depressive symptoms. CES-D scores of 16 or greater reflect moderate or greater symptoms of depression (Radloff, 1977). A cut-point of 16 on the CES-D has very good sensitivity and specificity for the prediction of current major depressive disorder (Beekman et al., 1997). Participants were only included in the analysis if their CES-D score (16 or higher for the elevated depressive symptom groups and 15 or lower for the non-depressive group), was consistent with their classification from the previously recorded BDI-SF score, resulting in the exclusion of 17 participants and final participant counts of: 20 high CES-D participants in the active attention-training group, 22 high CES-D participants in the placebo training control group, and 33 in the low CES-D control group.

Attention Training

This task was designed to train participants' attention toward positive information (i.e., words) using a modified dot-probe paradigm. The task used neutral and positive words from the Affective Norms for English Words list (ANEW; Bradley & Lang, 1999). Words were matched for letter length and frequency of use in the English language. Therefore, the only differences between the list of positive and neutral words were valence and arousal.

The attention-training task is displayed in Figure 3.1. Each trial of the task began with a 500-ms presentation of a fixation-cross. Following the cross, a pair of stimuli, a positive word and a neutral word, were randomly presented to the right and the left side of the computer screen for 1000-ms. A dot-probe (i.e., * or **) appeared behind one of the previously displayed words. This probe appeared on the screen until the participant pressed one of two response buttons to indicate the identity of the probe (1 or 2 asterisks). In the active training condition, the probe was presented in the location associated with the positive word on 85% of the trials and the neutral word on 15% of the trials. In the placebo training condition, the probe was presented in the location of the neutral word on 50% of the trials and in the location of the positive word on 50% of the trials. In both conditions, the positive word appeared randomly and equally on either side of the screen. As in previous research (Wells & Beevers, 2010) we used 85% positive rather than 100% in the training condition to keep the intent of the study from being transparent.

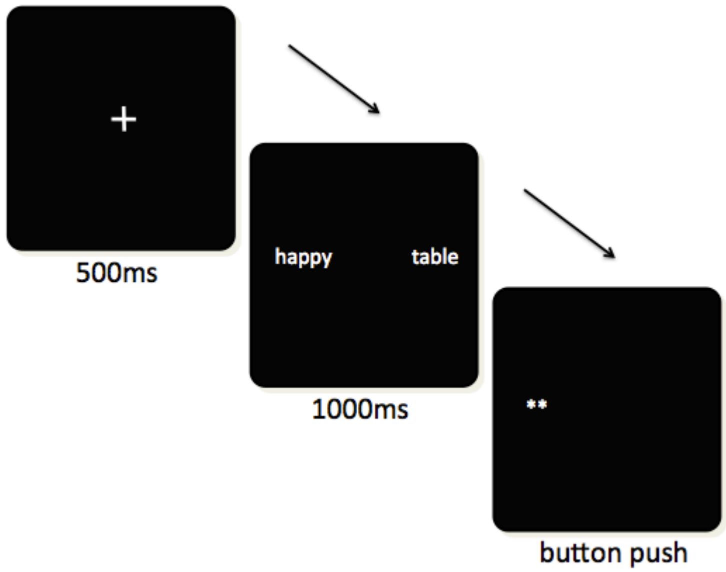

Figure 3.1: Attention Training Details.
In the placebo training condition the positive and neutral words each preceded the dot-probe with equal probability. In the active training condition the positive word preceded the dot-probe on 85% of trials.

Decision-Making Task

The decision-making task was identical to the history-independent decision-making task used in Chapter 1 (Figure 1.3). Participants performed a total of 150 trials, and were told nothing about the nature of the reward structure. In this two-option task, the average reward for the sub-optimal option is 55 points (units of oxygen), while the average reward for the optimal option is 65 points. However, because the standard deviation around the mean reward for each option is 15 units it is not the case that the optimal option yields a larger reward on every trial.

RESULTS

The mean CES-D scores for the active-training and placebo-training groups were 35.20 and 33.23, respectively. These did not differ significantly, $t(40) = .800$, $p = .429$, Cohen's $d = .252$. The mean CES-D score for the low CES-D group was 7.70, significantly lower than both the active training and placebo training groups (ps $< .001$).

Performance in the decision-making task was measured by analyzing the proportion of trials on which participants selected the optimal choice (the higher average reward) throughout the experiment. We used one-sample t-tests to determine whether performance significantly exceeded chance. Performance exceeded chance in the active attention training group ($M = .69$), $t(19) = 6.527$, $p < .001$, Cohen's $d = 2.995$, the placebo training group ($M = .61$), $t(21) = 3.118$, $p = .005$, Cohen's $d = 1.361$, and the non-depressive group ($M = .72$), $t(32) = 7.595$, $p < .001$, Cohen's $d = 2.685$. Thus, all groups learned to select the optimal choice.

We next used an ANOVA to examine the effect of group (placebo training, attention training, low CES-D) on the proportion of optimal selections (Figure 3.2). We observed an overall effect of group, $F(2,72) = 3.786$, $p = .027$, partial-$\eta^2 = .095$. There was also a significant linear contrast, $F(1,72) = 7.472$, $p = .008$, partial-$\eta^2 = .094$. As predicted, the participants who received placebo training selected the optimal choice less often than the low CES-D group, $t(53) = 2.573$, $p = .013$, Cohen's $d = .707$. Also as predicted, the participants who received placebo training selected the optimal choice less often than the participants who received active attention training $t(40) = 1.828$, $p = .06$, Cohen's $d = .578$. There was not a statistically significant difference in performance across the attention-trained participants and the low CES-D control group, $t(51) = .786$, $p = .436$, Cohen's $d = .220$.

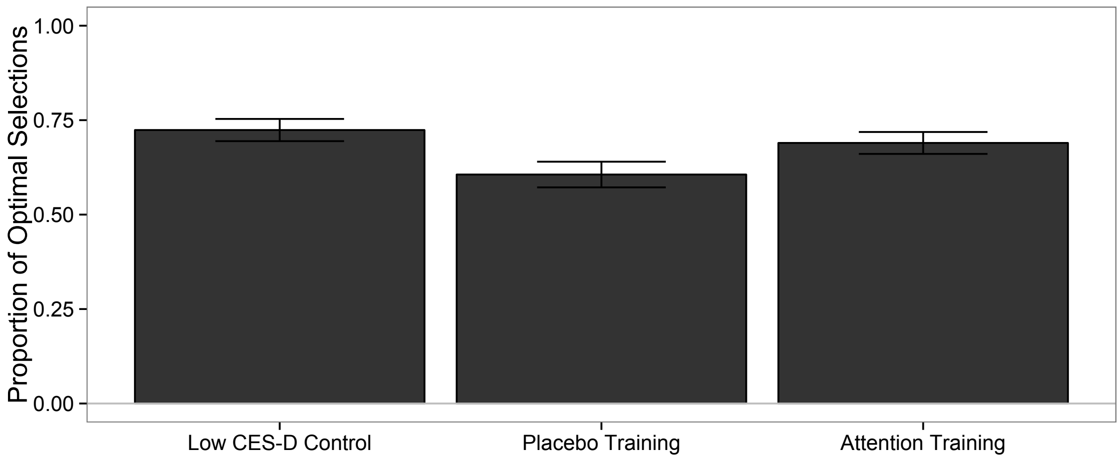

Figure 3.2: Chapter 3 Experiment 1 Performance.
Performance measured by proportion of optimal selections in the decision-making task. Error bars represent standard error of the mean.

The mood scores that were collected before and after the training procedure were also analyzed. Participants rated their current mood on two nine-point scales, from 'not happy at all' to 'very happy', and from 'not sad at all' to 'very sad'. Pre and post mood scores were compared for both the placebo training and active attention training groups using paired t-tests. The pre and post mood scores were not significantly different for either question for either group (*p*s>.1), indicating that changes in decision-making performance were not attributable to conscious changes in mood.

We also looked at correlations between CES-D score and performance on the decision-making task. Across all subjects who did not receive active attention training (low CES-D controls and high CES-D placebo training) CES-D scores were negatively correlated with task performance as indicated by proportion of optimal selections $r(53) = -.296$, $p = .03$. Interestingly, this trend was present in the non-depressed group, $r(31) = -.339$, $p = .05$, indicating that depressive symptoms may have a negative relationship with decision-making performance even at levels below the standard CES-D cutoff for depression. Correlations within the active training and placebo training groups were not significant (*p*s > .1).

Modeling

In the present study we use a variation of the Reinforcement Learning model to focus on learning from positive and negative information. This differs from previous chapters in that we are focusing on differences within the reinforcement-learning model, rather than reliance on the RL model relative to the heuristic-based WSLS model. We focus on the more complex RL model because we want to know how attention training modifies attention to rewards in the decision-making task.

The basic RL model accounts for decision-making behavior by updating expected reward values (EVs) for each option, i, on each trial, t, in Equation 3.1, based on prediction error δ:

$$\delta = r(t) - EV_{i,t} \quad (3.1)$$

Prediction errors are used to update EVs each time an option is chosen based on the following update rule:

$$EV_{i,t+1} = EV_{i,t} + \alpha \cdot \delta \quad (3.2)$$

The recency parameter (α), $0 \leq \alpha \leq 1$, weighs the degree to which participants update the expected values for each option based on their most recently received rewards. The expected values for each option are used to determine the probabilities for selecting each option by the Softmax decision rule (Sutton & Barto, 1998):

$$P(a_i, t) = \frac{e^{[\theta \cdot EV(a_i, t)]}}{\sum_{j=1}^{2} e^{[\theta \cdot EV(a_j, t)]}} \quad (3.3)$$

Where θ is an inverse temperature parameter representing the degree to which the option with the highest EV is chosen. Higher values of θ indicate that the highest valued option is chosen more often.

Individuals with depressive symptoms show enhanced punishment processing but deficient reward processing. Punishments are directly associated with negative prediction errors and rewards with positive prediction errors. To explore positive and negative reward prediction errors mechanistically we extended the model to account separately for positive and negative prediction errors. We let the model freely estimate two learning rate parameters that were used to update EVs in Equation 3.2 when prediction errors were positive (α_{pos}) or negative (α_{neg}).

One aspect of standard RL models is an assumption that on any given trial EVs for each option are represented by a single numerical value. An alternative assumption is that EVs are represented in the form of distributions around a mean value, rather than an exact single value. This assumption has been highlighted in recent RL and associative learning work (Doll, Jacobs, Sanfey, & Frank, 2009; Frank, Doll, Oas-Terpstra, & Moreno, 2009; Kruschke, 2008), and is likely more realistic in environments with variable rewards provided on each trial. This model assumes that the mean EV for the distribution of EVs is a recency-weighted average of past rewards for each option, as updated in Equation 3.1, and that Noise (*N*) around each mean is a recency-weighted average of the squared prediction errors on each trial:

$$N_{i,t+1} = N_{i,t} + \alpha_N \cdot [\delta^2 - N_{i,t}] \quad (3.4)$$

The degree to which the noise estimates are updated based on the most recent prediction errors is modulated by a recency parameter (α_N), $0 \leq \alpha_N \leq 1$, similar to how EVs are updated in Equation 3.2 above. We also fit the model with separate α_N parameters for trials with positive and negative prediction errors. This approach is similar to recent approaches that have approximated noise, or the variance in the most likely outcome for each choice option by tracking the variance in recent outcomes (Doll et al., 2009; Nassar, Wilson, Heasly, & Gold, 2010).

The initial N estimate for each option (N_0) is a free parameter that represents initial uncertainty regarding the average reward provided by each option. The Extended RL model includes this noise term in the Softmax rule to allow the model to account for behavior where participants select options that they have greater or lesser uncertainty about in the following decision rule:

$$P(a_t) = \frac{e^{[\theta \cdot EV_{a,t} + \theta_N \cdot \sqrt{N}_{a,t}]}}{\sum_{j=1}^{2} e^{[\theta \cdot EV_{j,t} + \theta_N \cdot \sqrt{N}_{j,t}]}} \qquad (3.5)$$

As in the Basic RL model we set a minimum value of 0 on θ, but we allowed θ_N to be positive or negative. Positive values indicate a greater preference for options that have greater uncertainty, while negative values indicate a greater preference for options with lesser uncertainty. Thus, the addition of the noise term allows us to account for behavior where participants attempt to reduce uncertainty regarding the noise around each expected reward value.

The Extended RL model has seven free parameters: α_{pos}, α_{neg}, $\alpha_{N(pos)}$, $\alpha_{N(neg)}$, N_0, θ, and θ_N, while the Basic RL model has two free parameters: α, and θ. We compared the relative fits of these two models using the Akaike Information Criterion (AIC) of each model, which rewards goodness of fit but also includes a penalty for increasing the number of free parameters (Akaike, 1974). This was done to ensure that the increase in relative fit of the model was not outweighed by the flexibility of additional parameters.

The final model that we fit, the baseline (or null) model, assumes fixed choice probabilities (Worthy et al., 2011; Gureckis & Love, 2009; Yechiam & Busemeyer, 2005). The baseline model has one free parameter that represents the probability of selecting one of the two options on any given trial. This model does not assume that participants learn from rewards given on each trial, yet it provides a good fit for data when participants repeatedly choose the same option (Gureckis & Love, 2009).

Model-Based Predictions

We believe that the observed behavioral differences can be attributed to increased attention to negative information in the placebo-trained group with elevated depressive symptoms, and that increased attention to negative information results in increased learning when prediction errors are negative, ultimately causing over-adjustment of the expected value for that option. In the extended RL model negative and positive reward prediction errors update the expected values for each option with separate learning rates (recency parameters), allowing the model to account for differential learning from positive and negative prediction errors. Consistent with previous work reporting hypersensitivity to negative feedback and punishment (i.e. Eshel & Roiser, 2010), we would expect increased attention to negative information to result in increased learning rates for negative prediction errors. As attention training is thought to reduce this bias, we would expect to see reduced learning rates (lower recency parameter) for negative prediction errors in the attention-trained group relative to the placebo-trained group.

Modeling Results

We fit each participant's data individually with the models detailed above. The models were fit on a trial-by-trial basis to the participant's response and the parameters were estimated using maximum likelihood. We used Akaike Weights (Wagenmakers & Farrell, 2004) to compare the relative fits of the models. The Akaike Weights are derived from Akaike's Information Criterion (AIC: Akaike, 1974), which is defined for each model *i* as:

$$\mathrm{AIC}_i = -2\mathrm{Log}L_i + 2V_i \quad (3.6)$$

where L_i is the maximum likelihood for model *i* and V_i is the number of free parameters in the model. Notice that the AIC measure penalizes the model for each additional free parameter.

The AIC values were used to generate the Akaike Weight for each of the three models for each participant. The relative likelihood, *L*, of each model, *i,* is computed using the transform:

$$L(M_i|\mathrm{data}) \propto \exp\{-\tfrac{1}{2} \cdot \Delta_i(\mathrm{AIC})\} \quad (3.7)$$

where Δ_i(AIC) represents the difference between the AIC for that model and the lowest AIC of all candidate models. The relative likelihoods of each candidate model are then normalized by dividing each of the likelihoods by the sum of all likelihoods for all *k* models:

$$w_i(AIC) = \frac{\exp\{-\frac{1}{2}\Delta_i(\mathrm{AIC})\}}{\sum_{k=1}^{K} \exp\{-\frac{1}{2}\Delta_k(\mathrm{AIC})\}} \quad (3.8)$$

These Akaike weights can be interpreted as the probability that the model is the best model for the data given the data set from the set of candidate models (Wagenmakers & Farrell, 2004).

We computed Akaike weights for each model for each participant. Figure 3.3 shows the average Akaike weights for each condition. The Extended RL model was clearly the best fitting model for all groups.

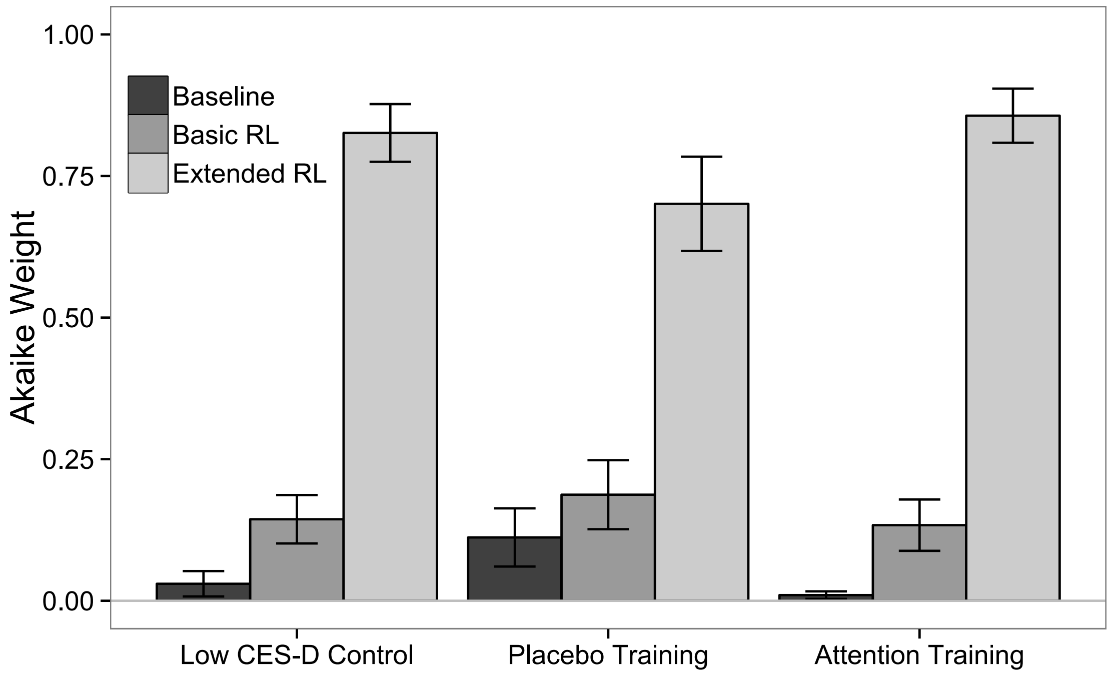

Figure 3.3: Chapter 3 Experiment 1 Modeling Results.
Akaike weights compare goodness of fit for the Baseline model, Softmax RL model, and Extended RL model. Higher Akaike weights indicate better fit. Error bars represent standard error of the mean.

Within the Extended RL model, our main parameters of interest were the learning rates for negative reward prediction errors and positive reward prediction errors (Figure 3.4). We observed no main effect of group within the learning rate for positive prediction errors ($p>.1$); however, we observed a main effect of group in learning from negative prediction errors $F(2,72) = 2.910$, $p = .061$, and a significant linear contrast, $F(1,72) = 5.755$, $p = .019$, partial-$\eta^2 = .074$. In decomposing this effect we found that the high CES-D placebo-trained group had significantly higher learning rates from negative prediction errors than the low CES-D group, $t(53) = 2.441$, $p = .018$, Cohen's $d = .670$; the same learning rate parameter for the attention-trained group was intermediate between these two groups.

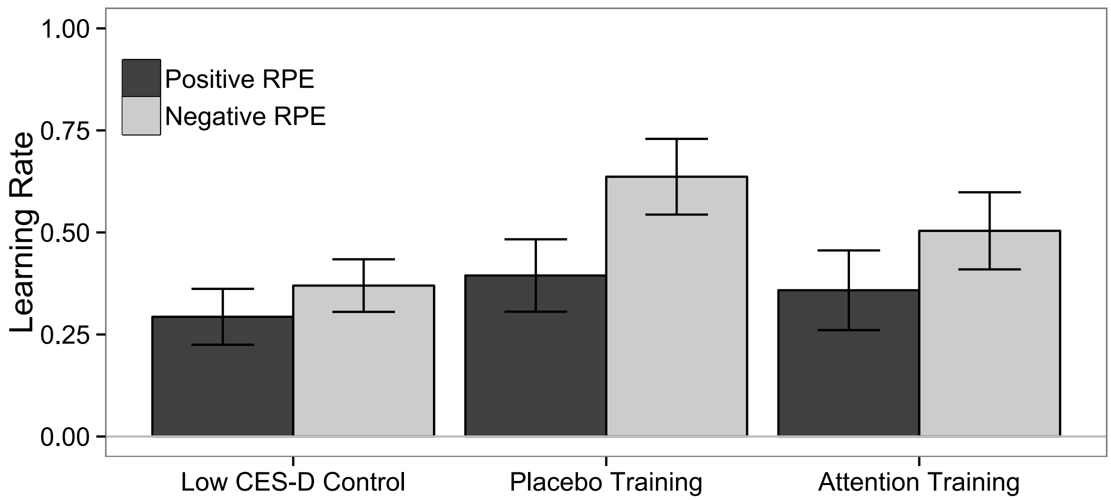

Figure 3.4: Chapter 3 Experiment 1 Learning Rates.
Learning rate parameter values for positive and negative reward prediction errors. Error bars represent standard error of the mean.

EXPERIMENT 1 DISCUSSION

The overriding aim of the present study was to determine whether an attention training procedure that was successful in ameliorating depressive symptoms might be used to attenuate the deficit in decision-making. In line with previous research (Beevers et al., 2013; Kunisato et al., 2012; Maddox et al., 2012) we found that individuals with elevated depressive symptoms showed performance deficits in maximizing rewards. Importantly, this performance deficit was significantly attenuated when given attention training towards positive stimuli prior to performing the decision-making task. In fact, performance of the active attention-trained group was no different from that of the low CES-D group.

It should be noted that the performance differences associated with depressive symptoms in this task were much greater than the performance differences observed in Beevers et al. (2013). This is probably attributable to the different reward structures underlying the previously published paper and the current study. The task in the previous paper had a clear separation between the optimal and suboptimal choices, where the lowest reward for the "good" option was still higher than the highest reward from the "bad" option. Thus, because the rewards never overlapped, the task was relatively easy and few performance or strategy differences were observed between the groups. These findings are consistent with the idea that depression has less of an effect on easier, automatic processing, but has a greater effect on more demanding tasks (Hartlage, Alloy, Vázquez, & Dykman, 1993; Hertel, 1994).

Computational modeling was utilized to better understand the strategies being used by each group to solve the decision-making task. Analysis of the best-fitting model parameters suggests that of the three groups, the placebo-trained group had the highest learning rate for negative prediction errors and the greatest discrepancy in learning from negative prediction errors relative to positive prediction errors. These findings indicate that individuals with elevated depressive symptoms may place too much weight on immediate rewards, particularly when these rewards are less than expected, resulting in overcorrection of their expected value for the rewarded option. This is consistent with previous research demonstrating that people with high depressive symptoms were more likely to alter their expected values based on recently received rewards (Beevers et al., 2013).

EXPERIMENT 2: ATTENTION TRAINING AND HISTORY-DEPENDENT DECISION-MAKING

In Experiment 1 we explored the effectiveness of attention training procedures in attenuating deficits associated with depression in history-independent decision-making. In the next experiment, we test this training mechanism on history-dependent decision-making. Critically, the history-independent decision-making task in Experiment 1 differs from the history-dependent task in that optimal performance relies on the use of automatic attention to recent rewards, not effortful memories of reward structures. It is thus unclear whether reflexive training benefits will generalize to a reflective decision-making task.

The history-dependent task, used in the present study, is widely used to assess reflective decision-making ability (e.g. Cooper, Worthy, Gorlick, & Maddox, 2013; Gureckis & Love, 2009; Maddox et al., 2012; Worthy et al., 2011). In this task, the rewards available on a given trial are dependent on the participant's recent history of choices. Optimal performance requires the participant to forego the larger immediate reward in order to maximize future rewards. In short, participants must retain information in working memory regarding the choices they make as well as the rewards that they receive for each choice, update the information when new rewards are received, and reflect back on their experiences to determine how rewards change over time.

One hypothesis for Experiment 2 is that the reflective decision-making deficit observed in individuals with elevated depressive symptoms is due to the same bias towards negative feedback and away from positive feedback that mediates the reflexive decision-making deficit. If this hypothesis is correct, the reflexive attention training procedure used in Experiment 1 should be successful in attenuating the deficit in the reflective decision-making task. Alternately, a hypothesis that we consider to be more likely is that the deficit in history-dependent decision-making is associated with deficits in reflective processes that will not be attenuated with attention-training mechanisms.

METHOD

Participants

One hundred and ten undergraduate students completed the study as a part of a research requirement for an introduction to psychology course. Participants completed the short form of the Beck Depression Inventory (BDI-SF; Beck & Steer, 1993) during a pre-testing survey battery. Participants whose scores were above 7 on the short form of the BDI-SF were contacted about participating (to fill the high depressive symptom groups), while participants whose scores were below 7 on the short form were also contacted about participating (for the low CES-D control group). Participants were not told that depression was a measure of interest and were given no information about their group status. See Table 3.2 for demographic information.

Table 3.2: Chapter 3 Experiment 2 demographic characteristics.

	Low CES-D	*High CES-D*	
	No Training	Placebo Training	Active Training
Sample size	37	37	36
Age: mean (sd)	21.54 (4.27)	19.32 (1.13)	19.17 (1.38)
Gender: m/f	14/23	13/24	13/23
CES-D: mean (sd)	8.54 (3.76)	29.24 (8.23)	27.56 (7.96)

**Standard deviations in parentheses.*

Materials and Procedure

At the beginning of the experimental session all participants completed a demographic form and a series of computer-based questionnaires that included the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977). The CES-D scores were used to validate previously recorded BDI scores. Following convention (Weissman & Sholomskas, 1977), participants who scored 15 or less on the CES-D were classified as having low depressive symptoms, and participants who obtained a 16 or greater were classified as having elevated depressive symptoms, reflecting moderate or greater symptoms of depression (Radloff, 1977). Participants with mismatched classification on the BDI-SF and CES-D were not included.

Participants with high depressive symptoms were assigned to placebo training (*n* = 37) or active attention training (*n* = 36). Non-depressive individuals only participated in the no training control condition (*n* = 37). Immediately following attention training, participants completed the decision-making task. The no-training group did not undergo training and completed the decision-making task immediately following the completion of demographic information and questionnaires.

Reflexive Attention Training

We used a variant of Wells and Beevers' (2010) attention training paradigm to implicitly direct attention towards positive information. The attention-training task is identical to the task used in Experiment 1.

Decision-Making Task

On each of the 150 trials the participant chose between two extraction systems, represented by a red system and a blue system. A bar on the right side of the screen would show the amount of oxygen that had been extracted on that trial, the collected oxygen would be moved to the cumulative tank, and the next trial would begin. Participants were given a goal to collect as much oxygen as possible. The rewards structure used in this experiment is identical to the history-dependent decision-making task reward structure in Chapter 1.

RESULTS

The mean CES-D scores for the groups with depressive symptoms (active, placebo) were 27.56 (SD = 7.96) and 29.24 (SD = 8.23), respectively. Mean CES-D score did not differ across the two training groups (p = .376). The mean CES-D score for the non-depressive group was 8.54 (SD = 3.76) and was significantly lower than both of the groups with depressive symptoms (ps < .001).

Performance in the decision-making task was measured using the proportion of trials on which the optimal choice was selected (Figure 3.5). We conducted an ANOVA on the effect of condition, which was non-significant $F(2, 107) = 2.158$, $p = .121$, partial-$\eta^2 = .039$. This suggests that active attention training was not effective in attenuating the reflective decision-making deficit observed in individuals with elevated depressive symptoms.

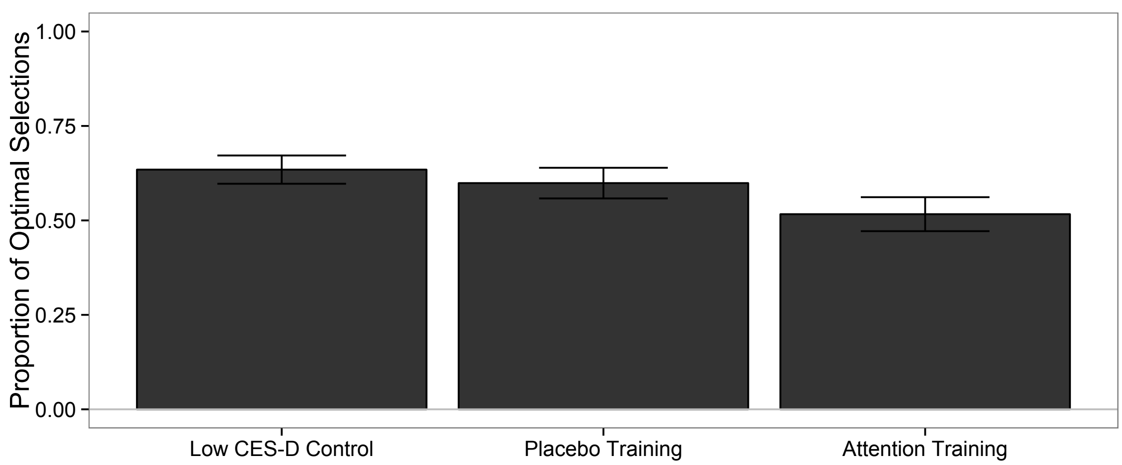

Figure 3.5: Chapter 3 Experiment 2 Performance.
Performance is measured as the proportion of trials on which the optimal choice is selected. Error bars represent standard error of the mean.

Modeling

The attention training mechanism had little effect on strategy utilization in the history-dependent decision-making task. Figure 3.6 shows the Akaike weight of each model for each of the three groups. The condition x model ANOVA indicated a non-significant interaction $F(4,321) = 1.791$, $p = .130$, partial-$\eta^2 = .022$ The Akaike weight of the WSLS model was numerically lower in the active attention training condition (M = .72), as compared to the placebo training condition (M = .84), although this difference was not significant (p = .210)

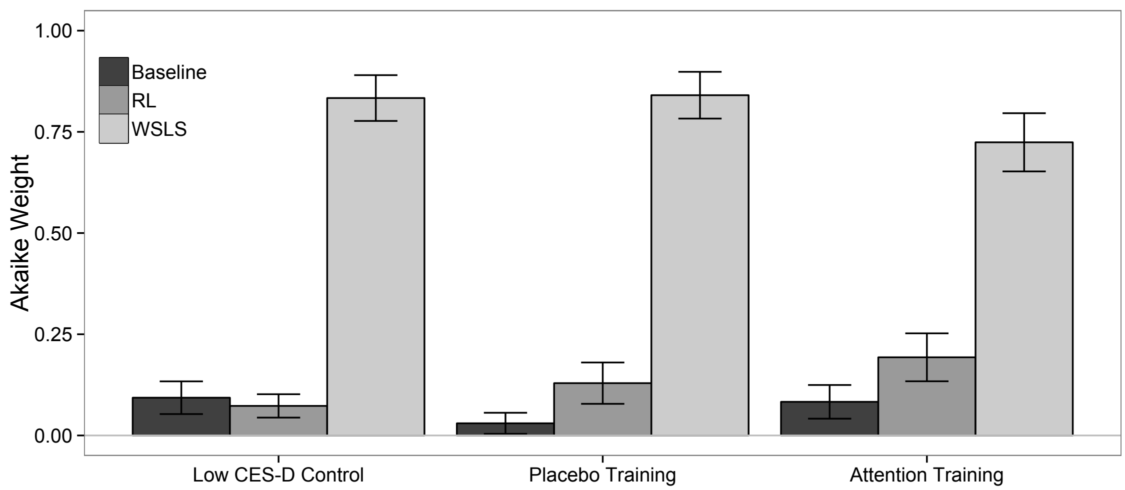

Figure 3.6: Chapter 3 Experiment 2 Modeling Results.
Akaike weights compare goodness of fit for the baseline model, RL model, and WSLS model. Higher Akaike weights indicate better fit. Error bars represent standard error of the mean.

DISCUSSION

The results of Experiment 2 indicate that the reflexive attention-training procedure previously used to attenuate depression-related deficits in reflexive decision-making (Cooper et al., 2014, Experiment 1) is not effective in attenuating deficits in reflective decision-making. We hypothesize that this lack of effect is due to different processes that mediate performance in the two types of decision-making tasks. Reflective decision-making, associated with the history-dependent task, is dependent on explicit processing (i.e. working memory) that is not affected by attention training.

CHAPTER 3 DISCUSSION

Individuals with major depression and elevated depressive symptoms face physical, social and cognitive challenges. The presence of depressive symptoms is associated with increased attention to negative information and decreased attention to positive information. This reward processing deficit has broad effects on cognition, including one's ability to make good decisions (Beevers et al., 2013; Kunisato et al., 2012; Maddox et al., 2012; Pizzagalli et al., 2008). Recent research suggests that these reward processing deficits may be malleable and can be attenuated with attention training (Wells & Beevers, 2010). In Experiment 1, we successfully used attention-training mechanisms to modify decision-making performance, resulting in improved decision-making performance.

The task used in Experiment 1 was a history-independent decision-making task in which the participant must integrate reinforcement history over time to determine which option has the highest expected value. The best-fitting model for this task was a variation of a reinforcement-learning model, a class of models that are commonly associated with implicit, automatic processing. As such, the task used in Experiment 1 is often referred to as a reflexive task. Alternately, reflective decision-making depends on the ability to utilize working memory resources to determine how rewards change over time, demonstrated in Chapter 1. In Experiment 2, we found that attention training toward positive stimuli is ineffective at attenuating the deficit in history-dependent decision-making that is associated with symptoms of depression (Maddox et al., 2012).

Taken together, the results of Chapter 3 indicate that attention-training mechanisms show promise for modifying cognitive behavior that specifically results from processing of rewards, particularly at an implicit level. In Chapter 4 we continue to explore the depression-related deficit in the history-dependent decision-making task. Given the reliance of this task on working memory and explicit processing (Worthy et al., 2012; Chapter 1), we hypothesize that successful attenuation of the history-dependent decision-making deficit will depend on methods to increase the engagement of working memory and explicit processes.

Chapter 4: Depression, Working Memory, and Decision-Making (Cooper, Gorlick, Worthy, Koslov, Beevers & Maddox, in prep)

A large body of work identifies cognitive deficits related to depressive symptoms in tasks that involve effortful, reflective information processing, such as problem solving (Elderkin-Thompson, Mintz, Haroon, Lavretsky, & Kumar, 2006), planning (Rogers et al., 2004), cognitive flexibility (Butters et al., 2004), and memory (Burt, Zembar, & Niederehe, 1995). With these cognitive difficulties in mind, it is perhaps unsurprising that decision-making deficits associated with depressive symptoms are observed in a number of studies. Work from our lab identifies deficits associated with depressive symptoms in multiple decision-making tasks (Blanco, Otto, Maddox, Beevers, & Love, 2013; Maddox, Gorlick, Worthy, & Beevers, 2012), including those that involve more automatic, reflexive processing (Cooper, Gorlick, Denny, Worthy, Beevers & Maddox, 2014), as well as robust deficits in effortful, reflective processing (Maddox et al., 2012). The focus of the current chapter is the observed deficit in reflective history-dependent decision-making (Maddox et al., 2012).

We hypothesize that the previously observed difficulty in reflective decision-making for individuals with elevated depressive symptoms is due (at least in part) to deficits in planning and working memory (Maddox et al., 2012). In the current work (Experiment 1) we test whether engaging in a high-demand reflective working-memory task will improve performance for individuals with elevated depressive symptoms in a subsequent reflective decision-making task.

The reflective decision-making task in this study requires participants to forego a higher immediate reward in order to maximize long-term rewards and is known to depend heavily on working memory processes (Worthy, Otto, & Maddox, 2012). Participants with working memory resources limited by a concurrent dual-task develop a preference for maximizing immediate reward and perform worse than participants who do not have the concurrent dual-task (Worthy et al, 2012). In the same decision-making task, individuals with elevated depressive symptoms perform worse than individuals without depressive symptoms (Maddox et al., 2012), a deficit that may be attributable to reduced working memory associated with depression (i.e. Christopher & MacDonald, 2005; Joorman and Gotlib, 2008).

Engagement of working memory shows transfer effects on subsequent reflective tasks (Chein & Morrison, 2010; Jaeggi, Buschkuehl, Jonides, & Perrig, 2008). For example, working memory training over the course of 8 to 19 days with a tailored *n*-back test leads to improvements in the ability to reason and to solve new problems (Jaeggi et al., 2008). Likewise, training with a novel working memory task over the course of four weeks promotes increases in reading comprehension (Chein & Morrison, 2010). The purpose of our working-memory procedure is to exercise working memory using a single-session procedure and to encourage the engagement of working memory resources in a subsequent decision-making task. While it is possible that this will increase working memory capacity, this is not our expectation. However, if this procedure is successful in producing short-term improvements in decision-making then a longer-term training study will be warranted.

We hypothesize that working memory engagement should enhance subsequent reflective decision-making performance. To test this hypothesis, we implement a modified automated operational span procedure (Ospan; Unsworth, Heitz, Schrock, & Engle, 2005), a task for which participants must remember sequences of letters that are presented in between simple math problems. During the retrieval phase, the letters must be recalled in the order that they were presented, requiring participants to reflect on the information that they stored in working memory. A similar procedure has been used in combination with a symmetry-span task as part of a working-memory training program (Harrison et al., 2013).

The goal of Experiment 1 is to attenuate the deficit observed in reflective decision-making by engaging working memory resources. To examine whether the level of working memory engagement interacts with subsequent reflective decision-making outcomes, we manipulated the quantity of information held in working memory across two conditions: a low span condition and a high span condition. The low span condition is designed to be less taxing on working memory. Participants in the low span condition are only asked to retain 3-4 items in working memory, similar to the working memory necessary to respond in the decision-making task according to only the most recently received rewards. Alternately, participants in the high span condition are asked to retain 6-7 items in working memory, practicing the skills necessary for good performance in a reflective decision-making task for which the rewards received across many trials must be remembered and compared.

EXPERIMENT 1: WORKING MEMORY ENGAGEMENT AND HISTORY-DEPENDENT DECISION-MAKING

We test the hypothesis that deficits in working memory processing are at the heart of the reflective decision-making deficit observed in individuals with elevated depressive symptoms. Individuals with elevated depressive symptoms complete a low or a high span procedure to engage working memory prior to completing the reflective decision-making task. We predict that high engagement of working memory before the decision-making task will attenuate the reflective decision-making deficit observed in individuals with elevated depressive symptoms.

METHOD

Participants

One hundred and forty-eight undergraduate students completed the study as a part of a research requirement for an introduction to psychology course. Demographic information can be seen in Table 4.1.

Table 4.1: Chapter 4 Experiment 1 demographics characteristics.

	Low CES-D	*High CES-D*		
	Control	Control	Low-Training	High-Training
Sample size	37	37	37	37
Age: mean (sd)	21.46 (3.99)	20.56 (3.89)	19.59 (1.77)	19.46 (2.04)
Gender: m/f	14/23	9/28	7/30	15/22
CES-D: mean (sd)	8.03 (3.88)	26.11(7.76)	29.57 (8.05)	29.51 (9.08)

**Standard deviations in parentheses*

Participants with high CES-D scores were randomly assigned to the high span working memory condition (n = 37) or low span working memory condition (n = 37). A second group of control participants with high CES-D scores (n = 37) and low CES-D scores (n = 37) were also included. Immediately following reflective working memory engagement, participants completed the reflective decision-making task. The control groups completed the decision-making task immediately following the completion of demographic information and questionnaires.

Reflective Working Memory Engagement Task

A visual representation of the working-memory task can be seen in Figure 4.1. On each trial, participants were first shown a math problem for 4000ms (e.g. (3 × 3) - 8 = ?). The math problems were simple and involve multiplication, division, addition, and subtraction. Following presentation of the math problem, participants were shown a number, representing a potential answer to the math problem, and were required to respond if the number was the correct answer by selecting “true” or “false”. Participants were provided feedback (correct/incorrect) and shown a letter ('F', 'H', 'J', 'K', 'L', 'N', 'P', 'Q', 'R', 'S', 'T', or 'Y'; sampled without replacement) for 2000ms, after which another math problem was displayed. After the presentation of 3–7 sets of math problems and letters, participants were asked to use the keyboard to click the order of the letters that they viewed in the last span. Participants were provided sequential feedback about their recall accuracy. Their math accuracy score was displayed on the screen (percentage accuracy) throughout the experiment, and participants were asked to keep their math accuracy above 85%.

Participants in the low span condition received spans of 3 and 4-letter length for a total of 22 spans with 75 letters. Participants in the high span condition received spans of letter length 6 and 7 for a total of 12 spans with 75 letters. The working memory task was performed on PC computers using Matlab software with Psychtoolbox 2.54 (Brainard, 1997; Pelli, 1997).

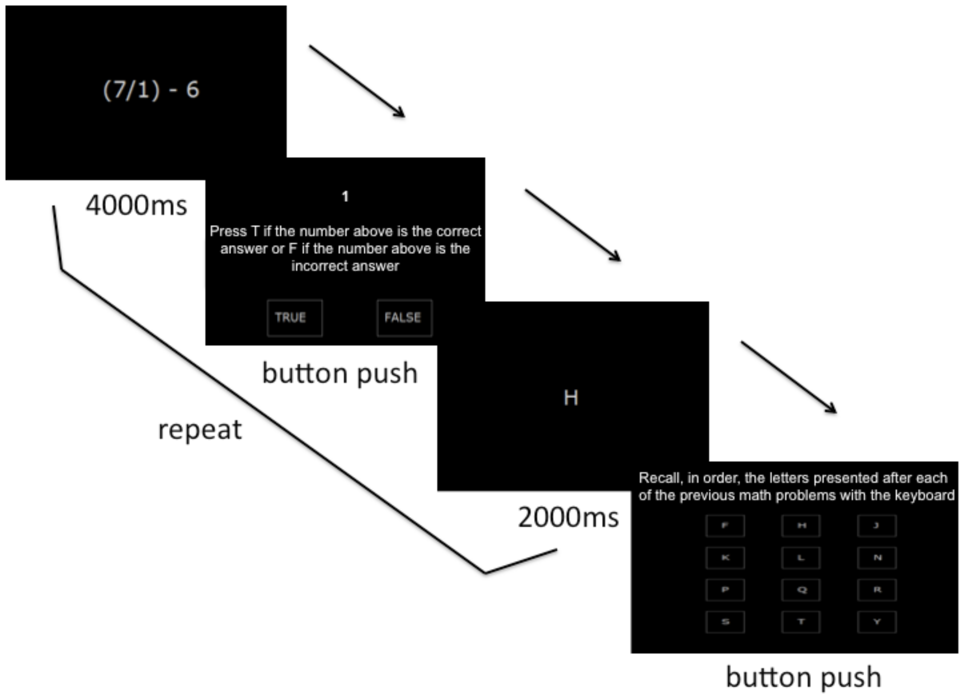

Figure 4.1: Working Memory Training Details.
In the low span condition participants received spans of 3-4 characters, while participants in the high span condition received spans of 6-7 characters.

RESULTS

The mean CES-D scores for the groups with depressive symptoms (high span, low span, and control) were 29.51 (SD = 9.08), 29.57 (SD = 8.05), and 26.11 (SD = 7.76), respectively. Mean CES-D scores did not differ across groups with depressive symptoms, $F(2, 108) = 2.103$, $p = .127$, partial-$\eta^2 = .037$. The mean CES-D score for the non-depressive group was 8.03 (SD = 3.88), significantly lower than all three of the groups with depressive symptoms (ps < .001).

Performance in the working-memory task was measured using the proportion of correct responses. As expected, performance in the low span condition was significantly better than performance in the high span condition ($M_{\text{high}} = .76$, $SD_{\text{high}} = .12$, $M_{low} = .92$,

SD_{low} = .08), $t(72) = 6.621$, $p < .001$, Cohen's $d = 1.561$, indicating that the low span condition was less taxing than the high span working memory condition.

Performance in the decision-making task was measured by analyzing the proportion of trials on which the optimal choice was selected. We first compared performance for the non-depressive group with the control group with elevated depressive symptoms to determine whether we replicated the performance deficit reported in Maddox et al. (2012). Consistent with Maddox et al., we observed a deficit in decision-making performance in individuals with elevated symptoms of depression (M = .52) relative to the low CES-D group (M = .63), $t(72) = 1.928$, $p = .058$, Cohen's d = .454. Next, we conducted an ANOVA to examine the effect of group (low CES-D control, high CES-D control, low span, and high span) on performance (Figure 4.2), observing a main effect, $F(3,144) = 2.681$, $p = .049$, partial-$\eta^2 = .053$.

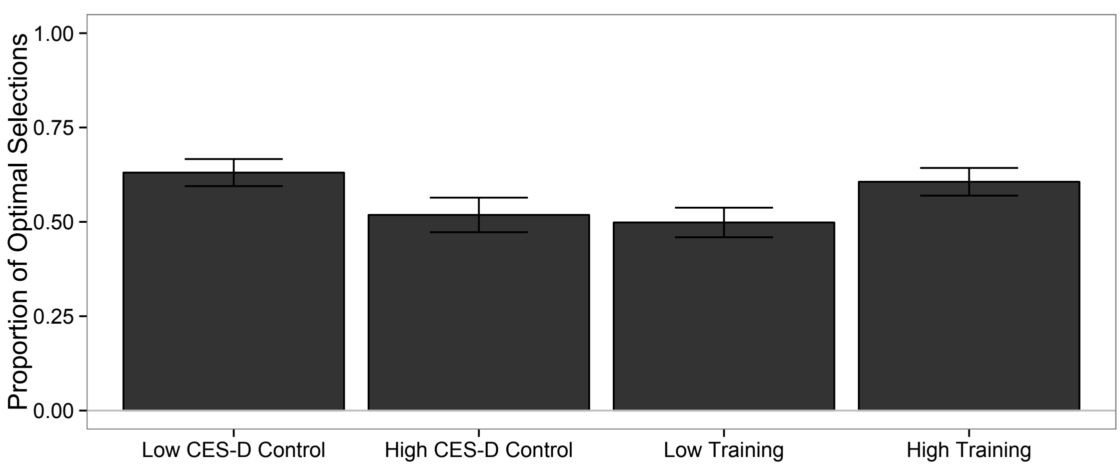

Figure 4.2: Chapter 4 Experiment 1 Performance.
Performance is measured as the proportion of trials on which the optimal choice is selected. Error bars represent standard error of the mean.

Individuals in the high span group selected the optimal choice more frequently (M = .61) than those in the low span group (M = .50), $t(72) = 2.010$, $p = .048$, Cohen's d = .474. Importantly, performance did not differ significantly between the high span group and the low CES-D control group ($p = .637$). Individuals in the low span condition also selected the optimal choice less frequently than the low CES-D control group (M = .63), $t(72) = 2.487$, $p = .015$, Cohen's d = .586, and were not significantly different from the high CES-D control group ($p = .741$). We repeated all of these analyses using points as the performance measure and all results replicated. We further examined these performance differences by analyzing the number of trials on which participants switched between options, streaks of increasing and decreasing option selections, and reaction times after positive and negative reward changes. However, none of these measures showed significant group differences (ps > .2).

Modeling

Each participant's data was fit on a trial-by-trial basis with the Baseline, Reinforcement Learning and Win-Stay Lose-Shift models described in detail in Chapters 1 and 3. In order to compare these models, the Akaike weight for each model was calculated for each participant, consistent with the methods and equations described in Chapter 3.

One possibility for the change in performance associated with the working memory task is that it encourages the use of reflective, heuristic-based strategies that are dependent on working memory (thus decreasing the use of reflexive, automatic strategies that often result in poor performance in this task). We examined whether strategy engagement was affected by the working-memory training procedure by comparing the Akaike weights for each model in each group. Consistent with previous chapters, we calculated the Akaike weight for each model for each participant and averaged these values across participants in each group. We found that a Condition x Model interaction, $F(6, 432) = 3.173$, $p = .005$, partial-$\eta^2 = .042$. The Akaike weight of the WSLS model was higher in the high CES-D group who completed the high-span working memory training procedure ($M = .90$) than those who did not complete a training procedure ($M = .74$), $t(72) = 1.862$, $p = .067$, Cohen's $d = .439$. The Akaike weight of the WSLS model in the high-span training condition was not different from the low CES-D group ($M = .90$), $p = .972$. The weight of the WSLS model for the low-span training group ($M = .77$) was intermediate between the no training and high-span training groups, and did not significantly differ from either groups, ps > .1.

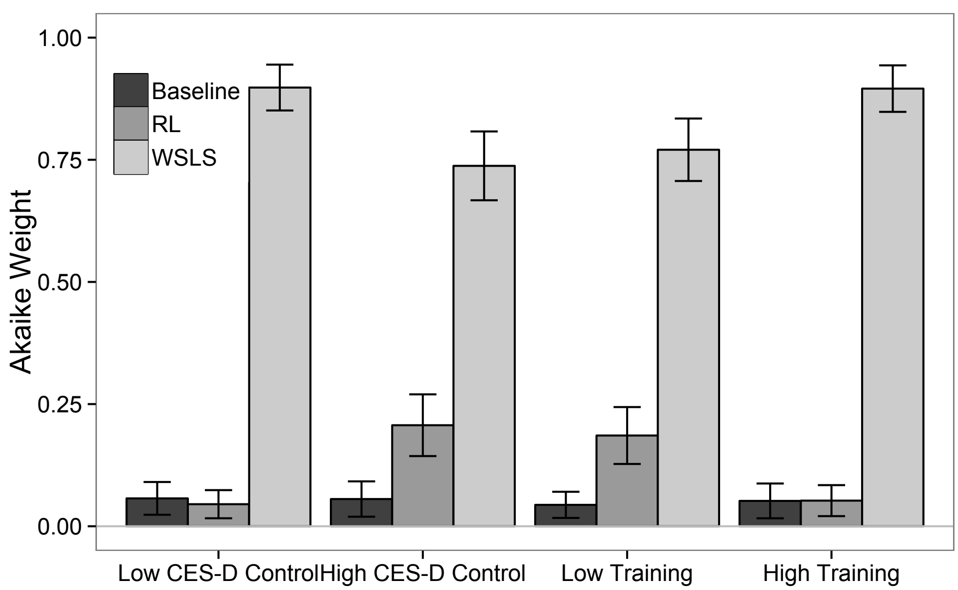

Figure 4.3: Chapter 4 Experiment 1 Modeling Results.
Akaike weights compare goodness of fit for the baseline model, RL model, and WSLS model. Higher Akaike weights indicate better fit. Error bars represent standard error of the mean.

EXPERIMENT 1 DISCUSSION

Many decisions benefit from a long-term focus and seeking courses of action that will be more rewarding in the future. People regularly make decisions in which they must weigh immediate rewards against delayed rewards concerning education, finances, and health choices. In the laboratory, individuals with elevated depressive symptoms show deficits in this type of decision-making (Maddox et al., 2012). Improving these individuals' ability to make decisions that maximize future reward could improve quality of life in the real world.

The current study explores the effects of reflective working memory engagement on reflective decision-making performance in individuals with elevated self-reported depressive symptoms. Replicating previous results (Maddox et al., 2012), we found that individuals with elevated depressive symptoms performed worse than individuals without elevated depressive symptoms in a reflective decision-making task. These findings are consistent with the idea that reflective history-dependent strategies depend on working memory (Worthy et al., 2012) and that depression is associated with working memory deficits (Christopher & MacDonald, 2005).

We also found that individuals with elevated depressive symptoms who completed a highly engaging working memory task performed better in a subsequent reflective decision-making task and were no different from those without depressive symptoms. This benefit was not observed in individuals who engaged working memory at lower levels, indicating that working memory tasks must be adequately challenging to show transfer effects in this domain.

EXPERIMENT 2: WORKING MEMORY ENGAGEMENT AND HISTORY-INDEPENDENT DECISION-MAKING

In the previous experiments and chapters, we have tested the effect of attention training toward positive stimuli on history-independent and history-dependent decision-making, and have tested the effect of working memory engagement on history-dependent decision-making, but we have yet to test the effect of the working-memory engaging task on history-independent decision-making. In the current experiment we test the effect of the high and low span working-memory engaging tasks on the history-independent decision-making task utilized in Cooper et al., 2014 (Chapter 3).

There are three clear possibilities regarding the effect of working memory training on history-independent decision-making. One possibility is that working memory training would only have an effect on subsequent tasks that depend entirely on reflective processing. In this case, our predominate finding of this series of studies would be that unique training mechanism are required to improve different types of decision-making, with little overlap between effects. Alternately, working memory training could affect performance in the history-independent task through two different routes. In Experiment 1 we found that completion of the high-span working-memory task led to increased utilization of WSLS, heuristic-based strategies. Likewise, the working memory task may also lead to enhanced use of heuristic-based strategies in the history-independent task.

Finally, the working memory task may affect performance in the history-independent task through a different mechanism than the shift in strategy observed in Experiment 1. In Chapter 3 we found that improved performance after attention training was associated with lowered learning rates, specifically when prediction errors were negative. Instead of responding to the most recently received rewards, rewards were integrated over time to develop accurate representations of the expected values of each option. These results are consistent with other work indicating that individuals with depression are responsive to delivery of single rewards, but fail to integrate rewards over time. Thus, one effect of the working memory task on reflexive strategies might be slower updating over a longer reinforcement history, or an increased ability to integrate reward information over time. We will use computational modeling to evaluate whether differences in learning rates can explain differences in performance, and whether differences are in response to positive or negative prediction errors.

EXPERIMENT 2 METHOD

In Experiment 2 we utilize the same working memory training procedure that we used in Experiment 1. Immediately following the working memory procedure, participants completed 150 trials of the history-independent decision-making task from Cooper et al. (2014).

Participants

One hundred and fifty-eight undergraduate students completed the study as a part of a research requirement for an introduction to psychology course. Demographic information can be seen in Table 4.2.

Table 4.2: Chapter 4 Experiment 2 demographics characteristics.

	Low CES-D	*High CES-D*		
	Control	Control	Low-Training	High-Training
Sample size	41	38	41	38
Age: mean (sd)	19.61 (1.73)	20.95 (4.01)	19.61 (2.84)	20.32 (4.19)
Gender: m/f	20/21	9/29	16/25	15/23
CES-D: mean (sd)	8.66 (3.84)	27.42 (7.90)	25.95 (7.67)	25.58 (8.52)

******Standard deviations in parentheses*

Results

Performance was assessed using the proportion of trials on which the optimal choice was selected. We first conducted an ANOVA to examine the effect of group (Low CES-D control, high CES-D control, low-span, high-span) on performance (Figure 4.4), observing a main effect, $F(3,154) = 3.138$, $p = .027$, partial-$\eta^2 = .058$. We directly compared the low CES-D and high CES-D groups to determine whether there was a deficit associated with depressive symptoms. The group with low CES-D scores selected the optimal choice ($M = .70$) more often than those with high CES-D scores ($M = .62$), $t(77) = 2.701$, $p = .008$, Cohen's $d = .616$. The group that completed the high-span working memory task performed better on the decision-making task ($M = .69$) than the no-training group $t(74) = 2.304$, $p = .024$, Cohen's $d = .536$. Those who received the low-span training ($M = .68$) also performed better than the no training group, $t(77) = 2.026$, $p = .046$, Cohen's $d = .462$. There were no performance differences between the low CES-D group, low-span training, and high-span training (ps > .5). As in Experiment 1, we did not observe any significant group differences in rates of switching between options, streaks of increasing and decreasing option selections, or reaction times after positive and negative reward changes (ps > .4).

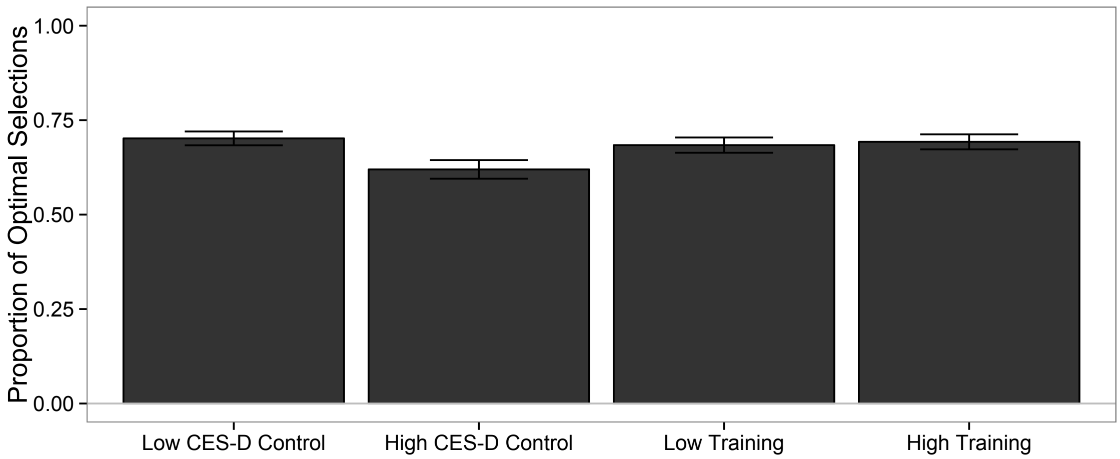

Figure 4.4: Chapter 4 Experiment 1 Performance.
Performance is measured as the proportion of trials on which the optimal choice is selected. Error bars represent standard error of the mean.

Modeling Results

We used the same model analysis from Cooper et al. (2014) and compared the relative model fit of the baseline, basic RL and Extended RL models[2] (Figure 4.5). The Extended RL model was again the best fitting model for all groups. Within the Extended RL model, our main parameters of interest were the learning rates for negative reward prediction errors and positive reward prediction errors (Figure 4.6). We observed no main effect of group within the learning rate for negative prediction errors ($p > .9$); however, we observed a significant main effect of group in learning from positive prediction errors $F(3,154) = 2.691$, $p = .048$, partial-$\eta^2 = .05$. The group that completed the high-span working memory training procedure was associated with the lowest learning rate (M = .24), which was significantly lower than the learning rate for individuals with high CES-D scores who did not receive training (M = .49), $t(74) = 2.962$, $p = .004$, Cohen's d =

[2] As Experiment 1 found differences in relative fit of the WSLS model, we also examined whether working memory training procedures affected the relative fit of the WSLS model in this task and observed no significant differences between groups.

.689. The group that completed the short-span training was fit by a learning rate for positive prediction errors (M = .34) that was in between the no training and high-span training groups, marginally lower than the no-training group (p = .097), and not significantly different from the high-training group (p = .231).

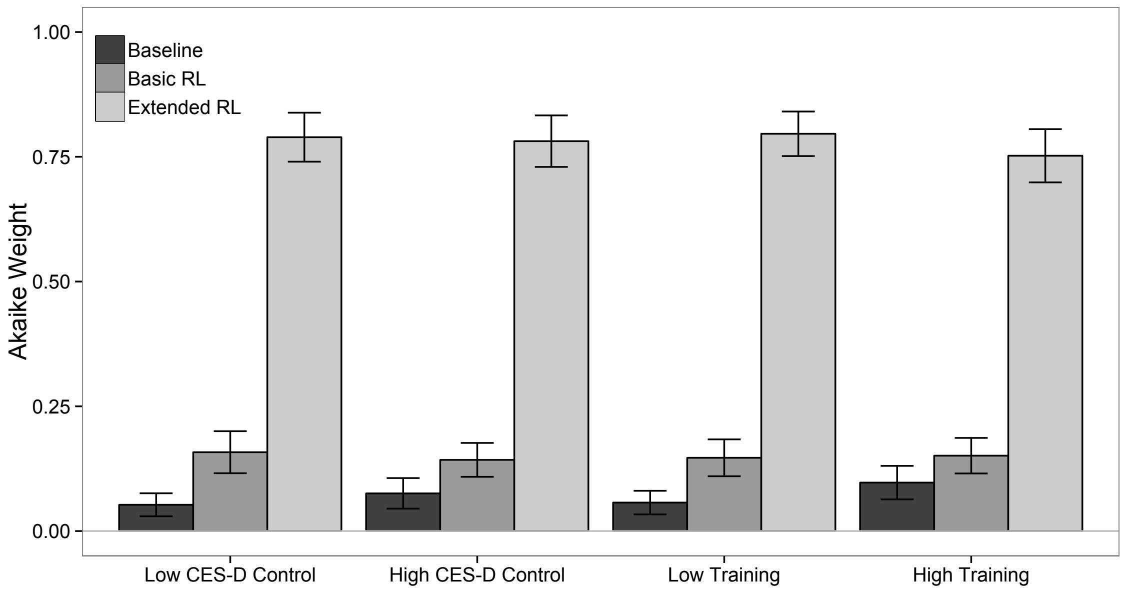

Figure 4.5: Chapter 4 Experiment 2 Modeling Results.
Akaike weights compare goodness of fit for the baseline model, Basic RL model, and Extended RL model. Higher Akaike weights indicate better fit. Error bars represent standard error of the mean.

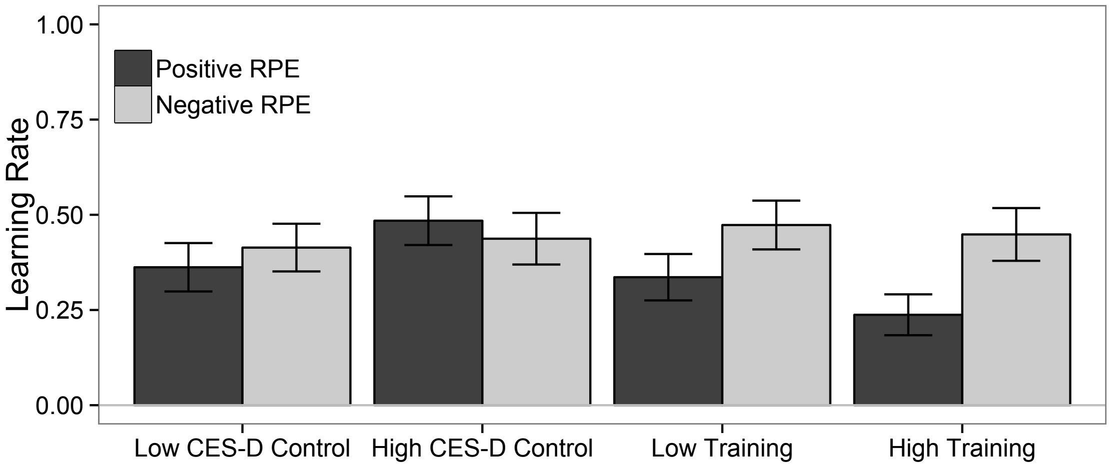

Figure 4.6: Chapter 4 Experiment 2 Learning Rates.
Learning rate parameter values for positive and negative reward prediction errors. Error bars represent standard error of the mean.

EXPERIMENT 2 DISCUSSION

In Experiment 2 we tested the effect of the working memory task utilized in Experiment 1 on the history-independent decision-making task for which attention training toward positive stimuli was effective at improving performance in individuals with elevated symptoms of depression. We found that engaging working memory, whether it was through high or low span lengths, was associated with improvements in performance in the history-independent decision-making task.

One critical component of reinforcement learning is the ability to integrate reward information over time: a component of reinforcement learning that is impaired in individuals with depression (Pizzagalli et al., 2008). Theories of response selection propose that the dorsal anterior cingulate cortex utilizes dopaminergic reward prediction error signals, integrating recent reinforcements to guide choice behavior (Holroyd and Coles, 2002, 2008). Interestingly, this region is also implicated in working memory tasks very similar to the task utilized in our study. Activation in the anterior cingulate cortex is correlated with the ability to correctly recall letters in the operational span procedure (Faraco et al., 2011).

The improvements in performance that we observed in our study are potentially attributable to lower learning rates indicating that participants were not overly responsive to the receipt of a single reward, but successfully utilized the rewards presented over several trials to form an understanding of the option that gives the better average reward. Future imaging work should examine the neural relationship between the working memory task and subsequent history-independent decision-making performance.

Chapter 4 General Discussion

In Chapter 4 we tested the effect of a working memory training procedure on subsequent decision-making performance. In these experiments we tested effects in two very different decision-making tasks, one that requires participants to observe how current selections affect future rewards over time, and one that only requires participants to select an option that gives the higher average reward. Perhaps surprisingly, we found that performance in both of these tasks was positively impacted by the working-memory engaging task.

It is important to note that the low-span working memory task was associated with better performance in the history-independent task, but not the history-dependent task. One possible explanation for this difference is that the history-dependent task could be considered more difficult than the history-independent task, if only judging by participants' performance (Chapter 1). Participants in this task learn the optimal strategy less quickly than the history-independent task, and perform at a lower level overall. Thus, the lower span task may only be successful in attenuating performance deficits in easier tasks.

The modeling results of these experiments indicate that the benefit of working memory training in the history-dependent task is associated with a shift from the utilization of sub-optimal reinforcement learning models to heuristic-based win-stay lose-shift models. The same shift was not observed in the history-independent task. In this case, changes in performance seem to be instead attributable to reduced learning rates. Lower learning rates indicate that the participant updates expected value less based on the reward prediction error. This decrease in learning rates can also be interpreted as an increase in the effect of more distant previous rewards on the current expected value, as expected values fluctuate less as rewards are received. It is particularly interesting that we observed a change in learning rates for positive prediction errors, but not negative prediction errors. This could be due to reward salience—that negative reward prediction errors are particularly salient and thus not modified with working memory training. The observation of differential effects on learning from positive and negative reward prediction errors is not surprising, given their different neural underpinnings. Dopaminergic neurons are believed to signal positive and negative reward prediction errors differently—with bursts in firing for positive reward prediction errors, and pauses for negative prediction errors (e.g. Niv, 2013). Future work should seek to determine the specific neural effect of working memory training, focusing on different effects on positive and negative reward prediction errors.

While the current work utilized neutral stimuli in our working memory procedure (i.e. letters), future work may benefit from the use of appropriate affective stimuli (emotional words and/or faces) in working memory training, which has been shown to improve affective control and emotion regulation (Schweizer, Hampshire, & Dalgleish, 2011; Schweizer et al., 2013). It is possible that incorporating affective stimuli will influence our effects.

We referred to the working memory task as a training paradigm; however, it is not training in the traditional sense that includes a goal of improving a skill. Our goal for the working memory paradigm was to encourage the use of cognitive resources in a subsequent task. As such, a description of "working memory priming" or "working memory induction" might have been more appropriate, but these descriptions also have associations that do not align with the goals of the current study. In the current work we did not expect to induce long-term improvements in working memory, and we could therefore only expect our effects to be short-lived. Future work would benefit from longer-term training mechanisms that do enhance working memory to determine whether effects in performance can be attributed to increased working memory or short-lived strategy modification. While decision-making performance was higher after one session of this working memory task, it is likely that long-term training could increase working memory capacity, further increasing cognitive performance.

Chapter 5: Long Term Training and Decision-Making

In Chapter 5 we present the preliminary findings from a long-term working memory training procedure on both history-dependent and history-independent decision-making. In Chapter 4 we established that the engagement of working memory through the completion of a difficult operational span task led to better performance in subsequent decision-making tasks. While it is exciting that we can produce changes in a single-session procedure, these benefits only last for a short period of time, and ultimately we would like to produce longer-lasting improvements in cognition. The goal of this study is to determine whether longer periods of training can lead to more persistent improvements in performance, and whether the valence of training stimuli affects performance in reward-based decision-making.

Previous work in working memory training with emotional material found that training led to transfer gains in other working memory tasks, but also produced gains in cognitive control over affective information on an emotional Stroop task (Schweizer et al., 2011). Training with emotional material also led to enhanced efficiency of fronto-parietal neural circuitry and enhanced emotion regulation (Schweizer et al., 2013). Incorporating positive stimuli into working memory training may strengthen the efficacy of training in tasks that require the processing of emotional information. Additionally, we may see an additional effect of valence in decision-making tasks in which positive rewards must be processed and remembered for optimal performance.

We hypothesized that working memory training would improve performance in both the history-dependent decision-making task and the history-independent decision-making task, consistent with the findings of Chapter 4. We also hypothesized that long-span training with positive stimuli would show the greatest effect in the history-independent task. We made these predictions based on the combined results of Chapters 3 and 4—hypothesizing that remembering positive words may have a similar effect to attention training on those who depend on reflexive processing, and those who depend on reflective processing would benefit from the working memory training aspect of the procedure.

METHOD

Participants

Participants were recruited from the University of Texas at Austin. Participants were invited to participate in our study if their CES-D score was above or equal to the cutoff of 16, BDI-short score above or equal to 7, and if their performance was below the 40^{th} percentile on the history-dependent decision-making task (based on previously collected samples). Seventy-five participants began the study, with 45 individuals participating to completion. Participants were compensated \$8 per hour with a \$2 per hour bonus for completing the experiment.

Table 5.1: Chapter 5 sample information.

	Sample Size	*CES-D Start*	*CES-D End*	*Gender*	*Completion Time (Days)*
Long Neutral	12	26.4 (11.3)	23.9 (9.2)	9 F/ 3 M	47.3 (9.8)
Long Positive	11	30.1 (7.6)	28.2 (11.2)	9 F/ 2 M	45.2 (11.1)
Short Neutral	9	27.8 (14.3)	25.1 (12.3)	7 F / 2 M	50.2 (12.0)
Short Positive	13	32.0 (9.4)	32.2 (14.0)	9 F / 4 M	53.1 (10.3)

**Standard deviations in parentheses*

Procedure

Participants were assigned to one of four working-memory training conditions. Participants were stratified by gender to obtain similar proportions of male and female participants in each group. The training paradigm consisted of short and long versions of the Operational Span task (similar to Chapter 4) over the course of 20 sessions. The working memory task was modified so that the to-be-remembered stimuli consisted of either positive or neutral words. For the short versions, participants were asked to remember spans of 3-4 words interleaved with math problems, while in the long condition participants were asked to remember spans of 6-7 words, Figure 5.1.

Two sets of words were used in this set of data. All words were selected from the database of Affective Norms for English Words (ANEW; Bradley & Lang, 1999). The first set was matched on first letter, length, arousal, and frequency of use from the Corpus of Contemporary American English (Davies, 2008), Table 5.2. The second set of positive and neutral words was additionally matched on concreteness from the MRC Psycholinguistics Database (Wilson, 1988), Table 5.3.

Table 5.2: Long-term training stimuli set 1.

Neutral Set 1				
	Valence	Arousal	Freq	Length
Application	4.69	5.62	16261	11.00
Cowboy	6.48	5.75	5127	7.00
Embark	6.47	5.83	951	6.00
Future	6.71	6.48	99552	6.00
Game	6.98	5.89	112175	4.00
Hire	5.77	5.63	9941	4.00
Interest	6.97	5.66	76043	8.00
Lava	4.43	5.57	2230	4.00
Pierce	4.35	5.81	3976	6.00
Recipe	6.70	5.60	9950	6.00
Skyscraper	5.88	5.71	645	10.00
Theater	6.69	5.86	24767	7.00
Average	6.01	5.78	30134.8	6.58
STDev	0.99	0.24	41013.4	2.23

Positive Set 1				
	Valence	Arousal	Freq	Length
Achievement	7.89	5.53	18432	11.00
Comedy	8.37	5.85	10206	6.00
Elated	7.45	6.21	755	6.00
Friend	7.74	5.74	72248	6.00
Glad	7.77	5.70	17817	4.00
Hero	7.59	6.41	13774	4.00
Inspired	7.15	6.02	13623	8.00
Love	8.72	6.44	152358	4.00
Pretty	7.75	6.03	74017	6.00
Riches	7.70	6.17	1743	6.00
Sweetheart	8.42	5.50	2753	10.00
Triumph	7.80	5.78	5526	7.00
Average	7.86	5.95	31937.7	6.50
STDev	0.44	0.32	45576.6	2.24

Table 5.3: Long-term training stimuli set 2.

Neutral Set 2	Valence	Arousal	Freq	Length	Concreteness
Avenue	5.50	4.12	17263	6.00	539.00
Chance	6.02	5.38	60050	6.00	254.00
Errand	4.58	3.85	759	6.00	411.00
Gender	5.73	4.38	24441	6.00	408.00
Humble	5.86	3.74	4326	6.00	231.00
Industry	5.30	4.47	69208	8.00	479.00
Lightning	4.57	6.61	6724	9.00	525.00
Patient	5.29	4.21	36137	7.00	487.00
Rough	4.74	5.33	13748	5.00	452.00
Salute	5.92	5.31	2085	6.00	471.00
Theory	5.30	4.62	41090	6.00	287.00
Wonder	6.03	5.00	32538	6.00	305.00
Average	5.40	4.75	25697.4	6.42	404.08
STDev	0.54	0.82	22719.0	1.08	107.94
Positive Set 2					
	Valence	Arousal	Freq	Length	Concreteness
Angel	7.53	4.83	8988	5.00	399.00
Comfort	7.07	3.93	14886	8.00	402.00
Elegant	7.43	4.53	8028	7.00	309.00
Gentle	7.31	3.21	8839	6.00	322.00
Humor	8.56	5.50	11236	5.00	601.00
Intimate	7.61	6.98	7842	8.00	281.00
Laughter	8.45	6.75	13262	8.00	411.00
Peace	7.72	2.95	47264	5.00	309.00
Reward	7.53	4.95	7338	6.00	396.00
Spring	7.76	5.67	45390	6.00	524.00
Truth	7.80	5.00	48466	5.00	261.00
Wedding	7.82	5.97	17340	7.00	509.00
Average	7.72	5.02	19906.6	6.33	393.67
STDev	0.43	1.26	16654.0	1.23	105.94

The experiment consisted of a pre-test assessment, training period, and post-test assessment. During the pre-test assessment, all participants completed a battery of questionnaires that included the CES-D (Radloff, 1977). During the pre-test, participants completed 150 trials of a history-dependent decision-making task with either paint or martian oxygen surface features. Participants also completed 150 trials of the history-independent decision-making task from Chapter 1. Other cognitive tasks and questionnaires, not discussed in this dissertation, were included in this study to assess memory and executive functioning.

Training consisted of 20 sessions[3] of the Ospan procedure (Figure 5.1). This procedure was identical to the procedure utilized in Chapter 4, with the exception that participants had to remember words instead of letters. Sample screen shots of the word recall portion of the experiment can be seen in Figure 5.2. The training procedure was presented in Python 2.7. The program was installed on each participant's laptop. Participants who did not have access to a laptop computer or who did not wish to have programs installed on their computer were loaned a lab computer for the duration of the experiment.

After completing their training sessions, participants returned to the lab for their post-test assessments. The post-test was identical to the pre-test, with the exception that surface features from the pre-test were counterbalanced with the post-test so that participants did not receive the same surface feature twice.

[3] Due to experimenter and computer error, some participants only completed 19 sessions.

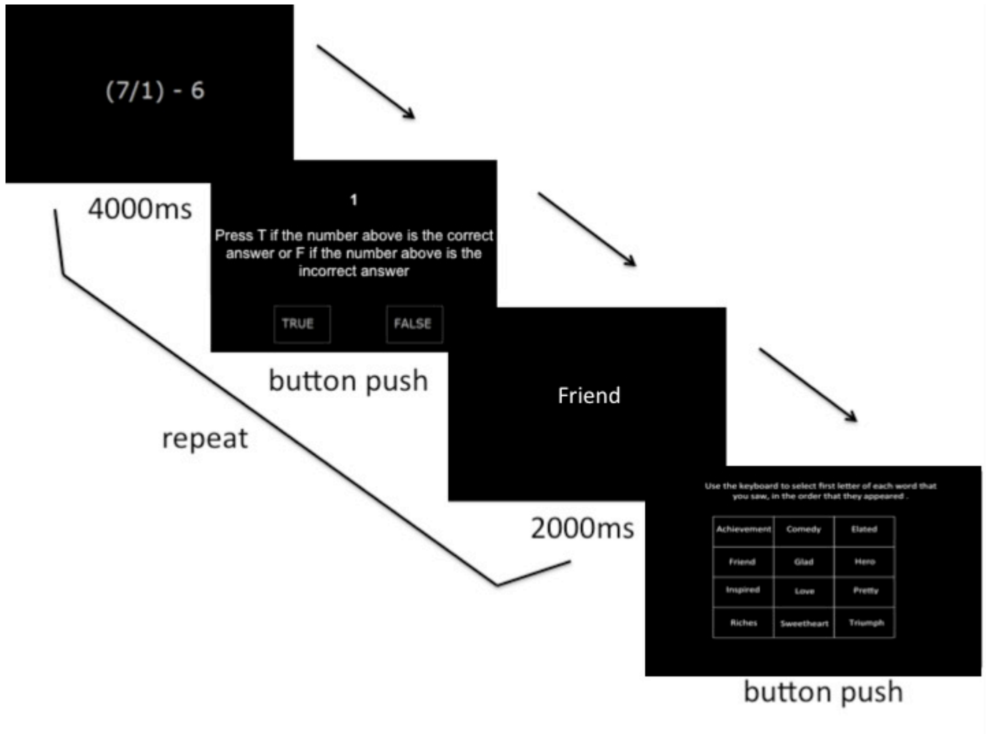

Figure 5.1: Long-Term Training Procedure.
Participants complete 20 sessions over a goal period of 5 weeks.

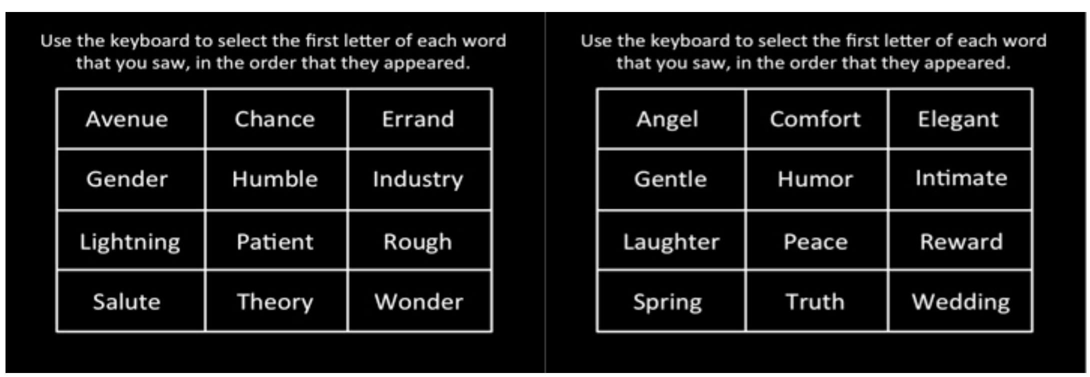

Figure 5.2: Long-Term Training Stimuli.
The operational span procedure was modified so that participants remembered words instead of letters.

RESULTS

History-Dependent Task

We examined performance in the history-dependent task by assessing the change in the number of points collected for each participant (post test – pre test). Positive values of this measure indicate that the participant improved their performance (Figure 5.3). Four participants' data (one in each condition) were excluded from this analysis for "button mashing"—selecting the same option on 99-100% of trials.

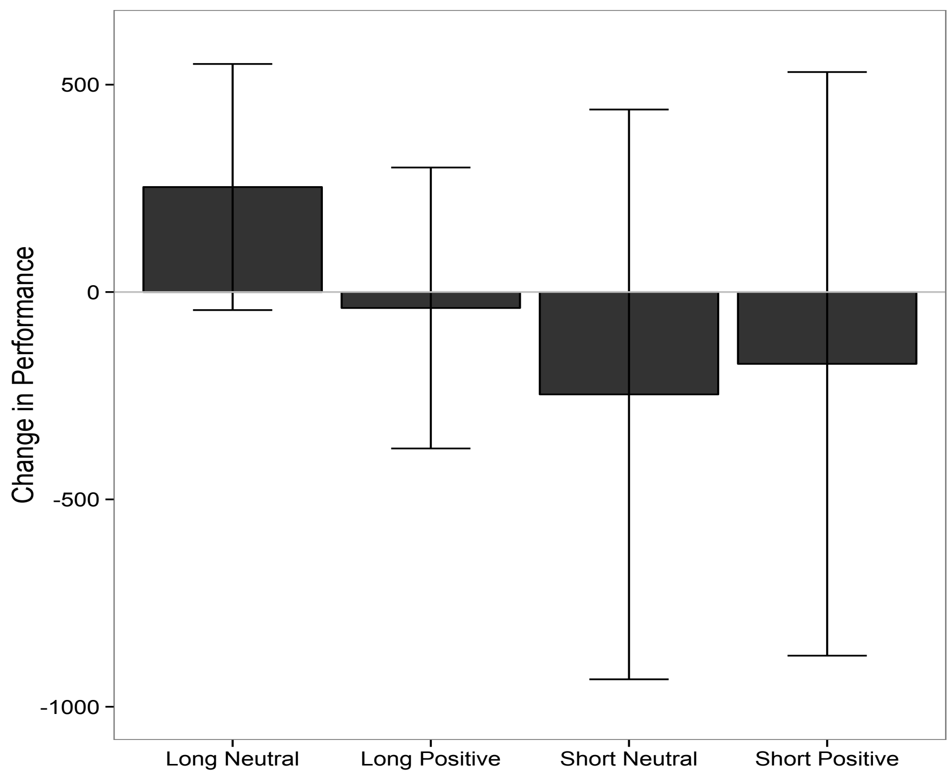

Figure 5.3: Chapter 5 History-Dependent Results.
Change in performance is measured by subtracting pre-test total performance from post-test total performance. Error bars represent standard error of the mean.

The only condition that showed an average positive improvement was the Long-Neutral group, however, this difference was not significantly different from zero using a one-sample t-test (p = .413).

History-Independent Task

We examined performance in the history-independent task by assessing the change in the number of points collected for each participant (post test – pre test). Positive values of this measure indicate that the participant improved their performance (Figure 5.4). Three participants were excluded from this analysis for selecting the same option on ≥ 99% of trials.

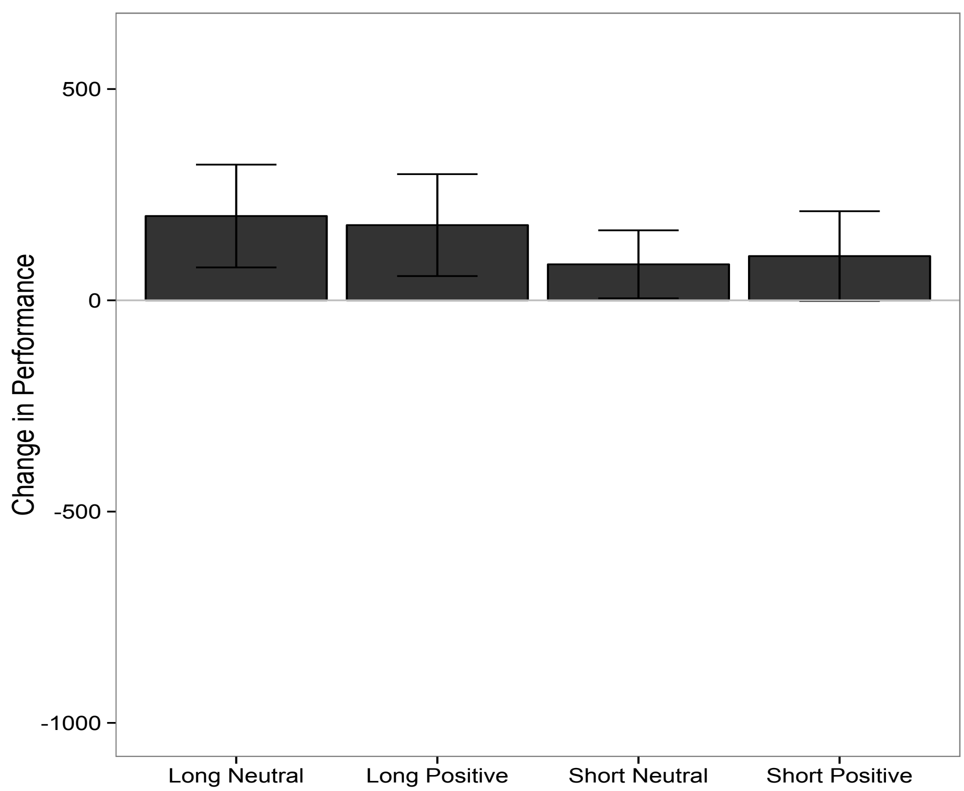

Figure 5.4: Chapter 5 History-Independent Results.
Change in performance is measured by subtracting pre-test total performance from post-test total performance. Error bars represent standard error of the mean.

The largest numerical improvement was observed in the Long Neutral condition, in which participants improved by an average of 189 points, followed by the Long Positive Condition (M = 178), Short Positive (M = 104) and Short Neutral (M = 85). These improvements were not significantly different from zero for individual groups (ps > .14), however, improvements were observed when collapsed across all participants who completed the Long-Span training conditions $t(13) = 2.281$, $p = .040$, Cohen's $d = 1.265$.

Training Performance

We analyzed performance in the memory portion of the operational span training procedure, as well as average reaction times for each session[4] (Figure 5.5). Performance did not change across sessions ($p = .827$), and session did not interact with condition ($p = .999$). We did observe a main effect of condition, $F(3, 655) = 16.220$, $p < .001$. Average performance was higher in the short-span conditions ($M = .92$) than the long-span conditions ($M = .88$), $t(734) = 5.564$, $p < .001$.

Reaction times showed a main effect of condition $F(3, 660) = 3.744$, $p = .011$, as well as a main effect of session, $F(19, 660) = 3.533$, $p < .001$. Reaction times were significantly higher in the first session than the last session, $t(75) = 6.663$, $p < .001$. Reaction times were also higher in the long-span training conditions than the short-span conditions, $t(734) = 2.933$, $p = .003$.

[4] For these analyses, we excluded reaction times on any response that took longer than 3.5 seconds, and sessions where performance was less than 50%, as we believed that values beyond these thresholds indicated that participants were not dedicating their full attention to the task.

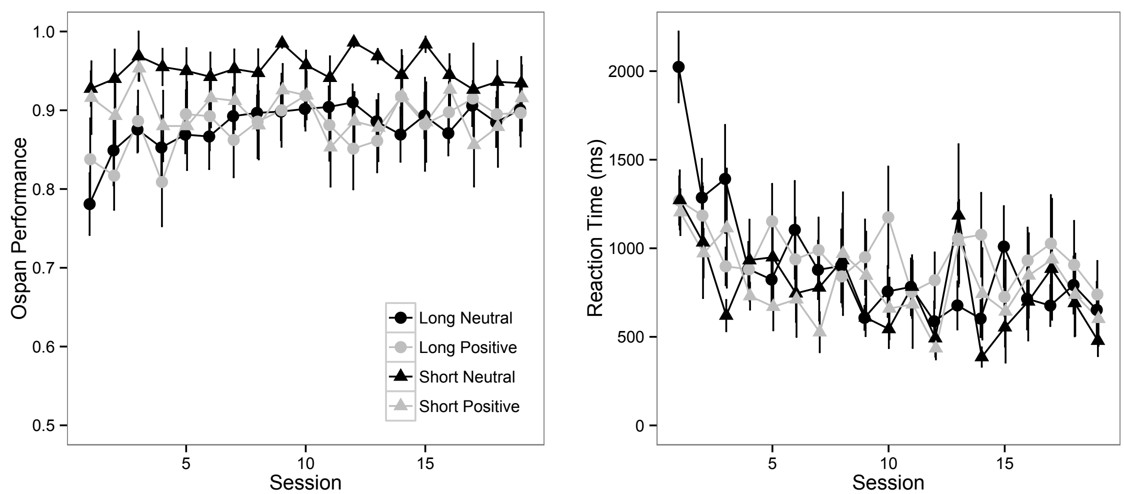

Figure 5.5: Training Performance.
Left: Accuracy in operational span memory trials. Right: Reaction times in training sessions. Error bars represent standard error of the mean.

Correlations

We examined correlations between improvements in the history-independent task, the history-dependent task, change in CES-D score, starting and ending CES-D scores, working memory training performance and response times[5], and time to completion. Improvements in the history-independent task were correlated with improvements in the history-dependent task, $r(22) = .437$, $p = .037$. Improvements in performance were not correlated with any other variables for either task.

CES-D Scores

Scores on the Center for Epidemiological Studies—Depression Scale (Radloff, 1977) were collected to measure the severity of depression symptoms. These scores were collected at the pre-test and post-test. We conducted a repeated measures ANOVA to

[5] Training performance measures included performance in each of the first and last recorded sessions and the difference between these sessions. Two participants did not have working memory data due to experimenter error and were excluded from correlations that included these measures.

determine whether CES-D scores differed across groups, whether they changed across time, and whether condition had a different effect on CES-D scores (time x group interaction). Neither the main effects ($p < .187$) nor the interaction were significant ($p = .843$).

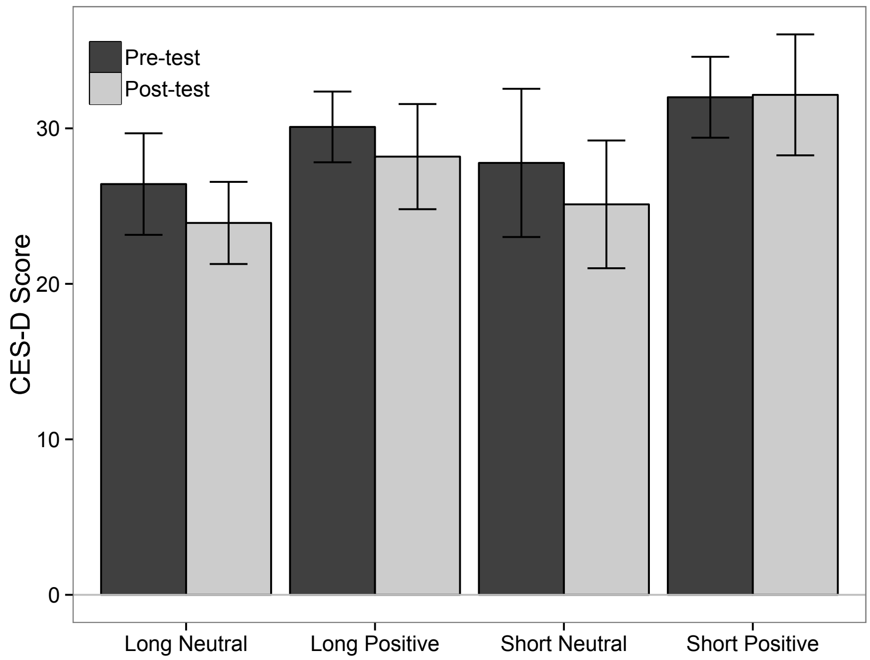

Figure 5.6: CES-D Scores.
CES-D Scores for each group, pre- and post- working memory training. Errors bars represent standard error of the mean.

Attrition Analysis

We experienced significant rates of participant dropout in this study. The completion rate was 60%. We are interested in identifying differences between those who completed the study and those who dropped out. In line with this interest, we analyzed initial CES-D scores, gender, and initial decision-making performance to determine whether differences existed between the two groups. The participants who did not complete the study had marginally lower initial CES-D scores ($M = 25.2$) than those who completed the study (M = 29.2), $t(72) = 1.687$, $p = .096$. Female participants were more likely to finish the study—68% of female participants finished the study, while only 44% of male participant who began the study completed it. The participants who did not complete the study also performed significantly worse on the history-dependent decision-making task $t(71) = 2.652$, $p = .010$ ($M_{\text{completed}} = 9136$, $M_{\text{Dropout}} = 8200$).

The difference in decision-making performance between those who dropped out and those who completed the study is particularly interesting. It is possible that those who dropped out would have shown the most benefit from the training. Thus, high dropout rates of individuals with poor history-dependent decision-making performance may have masked potential training effects.

CHAPTER 5 DISCUSSION

In this experiment we tested the effects of longer-term working memory training. Individuals with self-reported symptoms of depression, as assessed by the CES-D and BDI, completed 20 sessions of a working memory training procedure. We assessed changes in decision-making performance in two tasks: a history-dependent task for which future rewards depended on previous choice history, and a history-independent task for which rewards only depended on the current selection.

Our preliminary results suggest that performance in the history-independent decision-making task is positively affected by long-span working memory training, with little difference emerging between the positive and neutral training conditions. We also found minimal changes in performance in the history-dependent task in any condition, although this lack of effect may be attributable to the subset of participants who did not complete the training study. The only positive change, though non-significant, was observed in individuals who completed the long-span procedure with neutral stimuli.

Together, these results suggest that the long-span neutral stimuli condition has the greatest promise for improving decision-making performance across tasks.

Analyses of performance measures and reaction times in the training procedure indicate that participants did not significantly improve their performance in the task, but did improve their reaction times. The lack of improvement in performance may be due to high levels of performance of many participants, even in the difficult condition. Future studies using these types of training procedures would benefit from the use of an adaptive training paradigm that increases the span length as participants improve. Additionally, interleaving the operational span procedure with other working memory training tasks such as *n*-back or digit span tasks may be more effective at keeping participants engaged and reducing attrition.

The greatest challenge in this study that should be considered in future work is the significant rate of participant dropout, which limited our sample size and prevented us from drawing strong conclusions. Future work should seek methods of improving retention, such as increased compensation or increased completion bonus. Changes in recruitment methods may also improve retention rates. Specifically, many of our participants were students. It is possible that the variable schedule of college courses and exams interfered with their training schedules. Recruiting a sample from the community may allow for more stable schedules and increased completion rates. Future studies may also benefit from performance bonuses for individual pre- and post- test measurements to increase participant engagement. Work with a larger sample could provide insights regarding the mechanism underlying improvements in these tasks, and could help identify specific characteristics that determine the individuals who will show the greatest improvements from working memory training.

Final Remarks and Future Directions

Under the dual-systems theory of learning, at least two different learning systems have been identified through which learning may be moderated: a *reflective* hypothesis-testing system, and a *reflexive* reinforcement learning system (e.g. Ashby & Alfonso-Reese, 1998). In this body of work we examined performance in tasks that are optimally mediated by both systems, including within-subject performance between the tasks, stability across time, effects of individual differences on task performance, and malleability of performance with targeted training measures.

Our findings in Chapters 1 and 2 indicate that performance in reflective and reflexive tasks is related, but not deterministic. When participants are free to engage any strategy, participants often utilize heuristic-based strategies in these tasks, while they shift to reflexive strategies under cognitive load. Individuals who perform poorly in reflexive decision-making tasks do not necessarily perform poorly in reflective decision-making tasks, yet they show a propensity to engage similar strategies. It is perhaps surprising that deficits in both tasks are associated with depression symptoms when performance in the two tasks is not positively correlated. This is likely attributable to the heterogeneity of depression—that a single disorder category contains members with different symptoms, etiological pathways, and comorbid conditions (Treadway & Zald, 2011). It is therefore likely that the deficits that we observe in these unique tasks are due to different underlying causes. With this in mind, future work should seek to assess changes within an individual, and to determine whether specific traits can predict deficits in either task or responsiveness to methods of improving decision-making performance.

Our findings highlight the importance of developing training mechanisms that are aligned with the underlying processes that are necessary for optimal task performance.

We found that modifying attention toward positive stimuli affected performance in reflexive tasks, while it was ineffective at attenuating reflective reward processing deficits. Alternately, engaging working memory through an operational span procedure affected performance in both reflexive and reflective decision-making tasks, with computational models supporting different mechanisms of this effect. The results of the current study, combined with our previous work, lead us to believe that deficits can be attenuated through methods that target the underlying source of the deficit. We would hypothesize that attentional training methods would likewise affect implicit, habitual processes, while working memory training methods would affect other reflective processes.

The effect of working memory training on the history-independent decision-making task is particularly interesting. If the history-independent task is considered to be an entirely reflexive task, then our findings do not align with the dual systems framework. This discrepancy highlights the difference between the decision-making tasks and the tasks used in the category learning literature. In our history-independent task, decent performance can still be attained using rules and heuristic-based processes, whereas these processes lead to poor performance in implicit category learning tasks. The critical aspect in classifying the history-independent task as reflexive is that good performance *can be achieved* using reflexive strategies. At this point, it is unclear whether the positive effects of working memory training on history-independent decision-making were from enhancements in reflective processing, or from enhancements in the memory components of reflexive processes (e.g. remembering expected values). This difference can be further teased apart in future work by examining effects of working memory training on history-independent decision-making under dual task conditions that force participants to utilize reflexive strategies. If improvements are still observed, we should reconsider the importance of memory in reflexive tasks.

Overall, this body of work demonstrates that decision-making performance is malleable. In Chapters 3 and 4 we found performance differences between groups simply by ordering tasks in a manner than encouraged the use of optimal strategies through carry-over effects. We hypothesize that the attention and working memory training procedures used in Chapters 3 and 4 worked through a priming mechanism that encouraged participants to engage different strategies. In Chapter 5 we found that long term working memory training did not improve history-dependent decision-making performance. We see two clear possibilities for this outcome. One possibility is that decision-making performance in this task is not dependent on working memory capacity, but dependent on strategy engagement that is affected by the activities that immediately precede the task (i.e. affected by priming, but not long-term training). The other possibility is that the effects of long-term training on the history-dependent task were masked by our high attrition rate, particularly of participants who performed poorly in the history-dependent task and who showed more potential for improvement.

It should also be noted that variability in task performance arises in individuals without depressive symptoms that cannot be attributed to depression. Future studies should evaluate the effect of these training mechanisms on individuals with normative emotion processing but poor reflective processing. We would expect that individuals without symptoms of depression, but with poor decision-making performance, could benefit from these paradigms.

Finally, it is important to note that our study population throughout these experiments consisted of undergraduate students with high self-reported symptoms of depression. It is unlikely that many of our participants would meet the criteria for major depression, limiting the generalization of our findings to clinical populations. While it is possible that findings would be more pronounced in clinically depressed populations, it is also possible that deficits associated with reward-processing would be blunted due to anti-depressant medications (e.g. Eshel & Roiser, 2010). Future studies would benefit immensely from the consideration of neural mechanisms that underlie these deficits, effects of medication, and advanced computational models to further understand the effects of training mechanisms on cognitive processing.

Throughout this series of studies, we find that decision-making performance between history-dependent and history-independent decision-making tasks is related and relatively stable, and that individuals depend on similar strategies in different tasks, particularly during early trials. We also find that high self-reported symptoms of depression are associated with poorer performance in both of these tasks. Importantly, these studies show that decision-making performance is malleable, and is affected by both attention-training mechanisms and working memory training. Our final experiment indicates that long-term working training has the potential to improve decision-making performance. In particular, long-span training with neutral stimuli showed the most promise. Future studies using this type of training would be useful in determining the extent of these benefits, and whether they extend to other types of cognitive tasks.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723.

Ahn, W. Y., Busemeyer, J. R., Wagenmakers, E. J., & Stout, J. C. (2008). Comparison of decision learning models using the generalization criterion method. *Cognitive Science*, *32*(8), 1376-1402.

Ashby, F. G., & Alfonso-Reese, L. A. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological review*, *105*(3), 442.

Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, *56*, 149–178.

Ashby, F. G., and Maddox, W. T. (2011). Human category learning 2.0. *Annals of the New York Academy of Sciences, 1224*, 147–161.

Ashby, F. G., and O'Brien, J. B. (2005). Category learning and multiple memory systems. *Trends in Cognitive Science. 9,* 83–89.

Beck, A. T. (1976). *Cognitive therapy and the emotional disorders.* Oxford, UK: International Universities Press.

Beck, A. T., & Steer, R. A. (1993). *Beck Depression Inventory: Manual*. San Antonio, TX: The Psychological Corporation.

Beekman, A. T. F., Deeg, D. J. H., Limbeek, J., Braam, A. W., De Vries, M. Z., & Tilburg, W. (1997). Criterion validity of the Center for Epidemiologic Studies Depression scale (CES-D): results from a community-based sample of older subjects in the Netherlands. *Psychological Medicine*, *27*(1), 231–235.

Beevers, C. G., Worthy, D. A., Gorlick, M. A., Nix, B., Chotibut, T., & Maddox, W. T. (2013). Influence of depression symptoms on history-independent reward and punishment processing. *Psychiatry Research*, *207*(1), 53–60.

Berridge, K. C., & Robinson, T. E. (2003). Parsing reward. *Trends in neurosciences*, *26*(9), 507–513.

Blanco, N. J., Otto, A. R., Maddox, W. T., Beevers, C. G., & Love, B. C. (2013). The influence of depression symptoms on exploratory decision-making. *Cognition*, *129*(3), 563–568.

Bradley, B. P., Mogg, K., & Lee, S. C. (1997). Attentional biases for negative information in induced and naturally occurring dysphoria. *Behaviour research and therapy*, *35*(10), 911–927.

Bradley, M.M., & Lang, P.J. (1999). Affective norms for English words (ANEW): Stimuli, instruction manual and affective ratings. Technical report C-1, Gainesville, FL. The Center for Research in Psychophysiology, University of Florida.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial vision*, *10*(4), 433–436.

Burt, D. B., Zembar, M. J., & Niederehe, G. (1995). Depression and memory impairment: A meta-analysis of the association, its pattern, and specificity. *Psychological bulletin*, *117*(2), 285–305.

Busemeyer, J. R., Wang, Y. M. (2000). Model comparisons and model selections based on generalization criterion methodology. *Journal of Mathematical Psychology*, *44*, 171–189.

Butters, M. A., Bhalla, R. K., Mulsant, B. H., Mazumdar, S., Houck, P. R., Begley, A. E., et al. (2004). Executive Functioning, Illness Course, and Relapse/Recurrence in Continuation and Maintenance Treatment of Late-Life Depression. *The American Journal of Geriatric Psychiatry*, *12*(4), 387–394.

Chandrasekaran, B.,Yi, H-G. & Maddox, W.T. (2014). Dual-learning systems during speech category learning. *Psychonomic Bulletin and Review, 21,* 488-495.

Chein, J. M., & Morrison, A. B. (2010). Expanding the mind's workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin & Review*, *17*(2), 193–199.

Christopher, G., & MacDonald, J. (2005). The impact of clinical depression on working memory. *Cognitive Neuropsychiatry*, *10*(5), 379–399.

Cleeremans, A. & Dienes, Z. (2008).Computational Models of Implicit Learning In Sun, R. (Ed.), *The Cambridge Handbook of Computational Modeling*,Cambridge, UK: Cambridge University Press, pp. 396-421.

Cooper, J.A., Gorlick, M.A., Denny, T., Worthy, D.A., Beevers, C.G., & Maddox, W.T. (2014). Training attention improves decision-making in individuals with elevated self-reported depressive symptoms. *Cognitive, Affective, & Behavioral Neuroscience, 14(2), 729-741.*

Cooper, J. A., Worthy, D. A., Gorlick, M. A., & Maddox, W. T. (2013). Scaffolding across the lifespan in history-dependent decision-making. *Psychology and Aging*, *28*(2), 505–514.

Davies, M. (2008). *The Corpus of Contemporary American English: 520 million words, 1990-present*. Available online at http://corpus.byu.edu/coca/.

Daw, N. D., Niv, Y., & Dayan, P. (2005). Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. *Nature neuroscience*, *8*, 1704–1711.

DeCaro, M. S., Thomas, R. D., and Beilock, S. L. (2008). Individual differences in category learning: sometimes less working memory capacity is better than more. *Cognition, 107*, 284–294.

Denburg, N. L., Tranel, D., & Bechara, A. (2005). The ability to decide advantageously declines prematurely in some normal older persons. *Neuropsychologia, 43*, 1099-1106.

Doll, B. B., Jacobs, W. J., Sanfey, A. G., & Frank, M. J. (2009). Instructional control of reinforcement learning: A behavioral and neurocomputational investigation. *Brain research*, *1299*, 74–94.

Doya, K., Samejima, K., Katagiri, K., and Kawato, M. (2002). Multiple model based reinforcement learning. *Neural Computation. 14,* 1347–1369.

Elderkin-Thompson, V., Mintz, J., Haroon, E., Lavretsky, H., & Kumar, A. (2006). Executive dysfunction and memory in older patients with major and minor depression. *Archives of Clinical Neuropsychology*, *21*, 669–676.

Ellis, A. J., Beevers, C. G., & Wells, T. T. (2011). Attention Allocation and Incidental

Recognition of Emotional Information in Dysphoria. *Cognitive therapy and research*, *35*(5), 425–433.
Eshel, N., & Roiser, J. P. (2010). Reward and Punishment Processing in Depression. *Biological psychiatry*, *68*(2), 118–124.

Faraco, C. C., Unsworth, N., Langley, J., Terry, D., Li, K., Zhang, D., ... & Miller, L. S. (2011). Complex span tasks and hippocampal recruitment during working memory. *NeuroImage*, *55*(2), 773-787.
Frank, M. J., Doll, B. B., Oas-Terpstra, J., & Moreno, F. (2009). Prefrontal and striatal dopaminergic genes predict individual differences in exploration and exploitation. *Nature neuroscience*, *12*(8), 1062–1068.
Glascher, J., Daw, N., Dayan, P., O'Doherty, J. P. (2010). States versus rewards: Dissociable neural prediction error signals underlying model-based and model-free reinforcement learning. *Neuron, 66,* 585-595.
Gotlib, I. H., & Krasnoperova, E. (1998). Biased information processing as a vulnerability factor for depression. *Behavior Therapy*, *29*(4), 603–617.
Gureckis, T. M., & Love, B. C. (2009). Short-term gains, long-term pains: how cues about state aid learning in dynamic environments. *Cognition*, *113*(3), 293–313.
Hakamata, Y., Lissek, S., Bar-Haim, Y., Britton, J. C., Fox, N. A., Leibenluft, E., et al. (2010). Attention bias modification treatment: a meta-analysis toward the establishment of novel treatment for anxiety. *Biological Psychiatry*, *68*(11), 982–990.
Hallion, L. S., & Ruscio, A. M. (2011). A meta-analysis of the effect of cognitive bias modification on anxiety and depression. *Psychological Bulletin*. *137*(6):940-58
Hartlage, S., Alloy, L. B., Vázquez, C., & Dykman, B. (1993). Automatic and effortful processing in depression. *Psychological bulletin*, *113*(2), 247–278.
Harrison, T. L., Shipstead, Z., Hicks, K. L., Hambrick, D. Z., Redick, T. S., & Engle, R. W. (2013). Working Memory Training May Increase Working Memory Capacity but Not Fluid Intelligence. *Psychological Science.*
Henik, A. & Tzelgov, J. (1982). Is three greater than five: The relation between physical and semantic size in comparison tasks. *Memory & Cognition 10,* 389-395.
Hertel, P. T. (1994). Depression and memory: Are impairments remediable through attentional control? *Current Directions in Psychological Science*, *3*(6), 190–193.
Holroyd, C. B., & Coles, M. G. (2002). The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychological review*, *109*(4), 679.
Holroyd, C. B., & Coles, M. G. (2008). Dorsal anterior cingulate cortex integrates reinforcement history to guide voluntary behavior. *Cortex*, *44*(5), 548-559.
Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory, *Proceedings of the National Academy of Sciences of the United States of America*. *105*(19), 6829–6833.
Joorman, J., & Gotlib, I. H. (2008). Updating the contents of working memory in depression: Interference from irrelevant negative material. *Journal of Abnormal*

Psychology, 117(1), 182-192.
Kessler, R. C., & Walters, E. E. (1998). Epidemiology of DSM-III-R major depression and minor depression among adolescents and young adults in the national comorbidity survey. *Depression and anxiety*, *7*(1), 3–14.

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Koretz, D., Merikangas, K. R., et al. (2003). The Epidemiology of Major Depressive Disorder: Results From the National Comorbidity Survey Replication (NCS-R). *Journal of the American Medical Association*, *289*(23), 3095–3105.
Knowlton. (1999). What can neuropsychology tell us about category learning? *Trends in cognitive sciences*, *3*(4), 123–124.
Knox, W. B., Otto, A. R., Stone, P., & Love, B. C. (2012). The nature of belief-directed exploratory choice in human decision-making. *Frontiers in Cognitive Science*, *2*, 398.
Kruschke, J. K. (2008). Bayesian approaches to associative learning: From passive to active learning. *Learning & Behavior*, *36*(3), 210–226.
Kuhnen, C. M., & Knutson, B. (2005). The neural basis of financial risk-taking. *Neuron, 47,* 763-770.
Kunisato, Y., Okamoto, Y., Ueda, K., Onoda, K., Okada, G., Yoshimura, S., et al. (2012). Effects of depression on reward-based decision-making and variability of action in probabilistic learning. *Journal of Behavior Therapy and Experimental Psychiatry*, *43*(4), 1088–1094.
MacLeod, C., Mathews, A., & Tata, P. (1986). Attentional bias in emotional disorders. *Journal of abnormal psychology*, *95*(1), 15–20.
Macleod, C., Rutherford, E., Campbell, L., Ebsworthy, G., & Holker, L. (2002). Selective attention and emotional vulnerability: Assessing the causal basis of their association through the experimental manipulation of attentional bias. *Journal of Abnormal Psychology*, *111*(1), 107–123.
Maddox, W. T. & Ashby, F.G. (2004). Dissociating explicit and procedural learning based systems of perceptual category learning. *Behavioural Processes, 66,* 309-322.
Maddox, W. T., Gorlick, M. A., Worthy, D. A., & Beevers, C. G. (2012). Depressive symptoms enhance loss-minimization, but attenuate gain-maximization in history-dependent decision-making. *Cognition*, *125*, 118–124.
Mathews, A., & MacLeod, C. (2005). Cognitive vulnerability to emotional disorders. *Annual review of clinical psychology*, *1*, 167–195.
Miles, S. J., & Minda, J. P. (2011). The effects of concurrent verbal and visual tasks on category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *37*(3), 588.
Mogg, K., & Bradley, B. P. (2005). Attentional Bias in Generalized Anxiety Disorder Versus Depressive Disorder. *Cognitive therapy and research*, *29*(1), 29–45.
Nassar, M. R., Wilson, R. C., Heasly, B., & Gold, J. I. (2010). An Approximately Bayesian Delta-Rule Model Explains the Dynamics of Belief Updating in a Changing

Environment. *The Journal of Neuroscience*, *30*(37), 12366–12378.
Niv, Y. (2013). Neuroscience: Dopamine ramps up. *Nature*, *500*(7464), 533-535
Nolen-Hoeksema, S. (2000). The role of rumination in depressive disorders and mixed anxiety/depressive symptoms. *Journal of abnormal psychology*, *109*(3), 504–511.
Nomura, E. M., Maddox, W. T., Filoteo, J. V., Ing, A. D., Gitelman, D. R., Parrish, T. B., et al. (2007). Neural correlates of rule-based and information-integration visual category learning. *Cerebral. Cortex 17*, 37–43.
Otto, A. R., Taylor, E. G., &Markman, A. B. (2011). There are at least two kinds of probability matching: evidence from a secondary task. *Cognition, 118,* 274-279.
Paul, E. J., & Ashby, F. G. (2015). A neurocomputational theory of how explicit learning bootstraps early procedural learning. *Basal ganglia: physiological, behavioral, and computational studies*.
Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial vision*, *10*(4), 437–422.
Pizzagalli, D. A., Holmes, A. J., Dillon, D. G., Goetz, E. L., Birk, J. L., Bogdan, R., et al. (2009). Reduced Caudate and Nucleus Accumbens Response to Rewards in Unmedicated Individuals With Major Depressive Disorder. *American Journal of Psychiatry*, *166*(6), 702–710.
Pizzagalli, D. A., Iosifescu, D., Hallett, L. A., Ratner, K. G., & Fava, M. (2008). Reduced hedonic capacity in major depressive disorder: Evidence from a probabilistic reward task. *Journal of Psychiatric Research*, *43*(1), 76–87.
Poldrack, R. A., & Packard, M. G. (2003). Competition among multiple memory systems: converging evidence from animal and human brain studies. *Neuropsychologia*, *41*(3), 245–251.
Radloff, L. S. (1977). The CES-D scale a self-report depression scale for research in the general population. *Applied psychological measurement*, *1*(3), 385–401.
Ridderinkhof, K. R., & van den Wildenberg, W. (2004). Neurocognitive mechanisms of cognitive control: the role of prefrontal cortex in action selection, response inhibition, performance monitoring, and reward-based learning. *Brain and Cognition*, *56*(2), 129–140.
Rogers, M. A., Kasai, K., Koji, M., Fukuda, R., Iwanami, A., Nakagome, K., et al. (2004). Executive and prefrontal dysfunction in unipolar depression: a review of neuropsychological and imaging evidence. *Neuroscience Research*, *50*(1), 1–11.
Samanez-Larkin, G. R., Gibbs, S. E. B., Khanna, K., Nielsen, L., Carstensen, L. L., & Knutson, B. (2007). Anticipation of monetary gain bus not loss in healthy older adults. *Nature Neuroscience, 10,* 787-791.
Samanez-Larkin, G. R., Kuhnen, C. K., Yoo, D. J., & Knutson, B. (2010). Variability in nucleus accumbens activity mediates age-related suboptimal financial risk-taking. *The Journal of Neuroscience, 30,* 1426-1434.
Schweizer, S., Hampshire, A., Dalgleish, T. (2011) Extending Brain-Training to the Affective Domain: Increasing Cognitive and Affective Executive Control through Emotional Working Memory Training. *PLoS ONE,* 6(9): e24372.
Schweizer, S., Grahn, J., Hampshire, A., Mobbs, D., Dalgleish, T. (2013). Training the

Emotional Brain: Improving Affective Control through Emotional Working Memory Training. *The Journal of Neuroscience,* 33(12), 301-5311.

Sears, C. R., Thomas, C. L., LeHuquet, J. M., & Johnson, J. C. S. (2010). Attentional biases in dysphoria: An eye-tracking study of the allocation and disengagement of attention. *Cognition & Emotion*, *24*(8), 1349–1368.

Seger, C. A. (2008). How do the basal ganglia contribute to categorization? Their roles in generalization, response selection, and learning via feedback. *Neurosci. Biobehav. Rev. 32,* 265–278.

Seger, C. A., and Cincotta, C. M. (2005). The roles of the caudate nucleus in human classification learning. *J. Neurosci. 25*, 2941–2951.

Seger, C. A., and Miller, E. K. (2010). Category learning in the brain. *Annual Review Neuroscience. 33,* 203–219.

Steyvers, M., Lee, M. D., & Wagenmakers, E. J. (2009). A Bayesian analysis of human decision-making on bandit problems. *Journal of Mathematical Psychology*, *53*(3), 168–179.

Stroop, R. J. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology, 18,* 643-66.

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement Learning: An Introduction*. Cambridge, MA: MIT Press.

Teasdale, J. D. (1988). Cognitive Vulnerability to Persistent Depression. *Cognition & Emotion*, *2*(3), 247–274.

Treadway, M. T., & Zald, D. H. (2011). Reconsidering anhedonia in depression: lessons from translational neuroscience. *Neuroscience & Biobehavioral Reviews*, *35*(3), 537-555.

Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior research methods*, *37*(3), 498–505.

Wadlinger, H. A., & Isaacowitz, D. M. (2008). Looking happy: the experimental manipulation of a positive visual attention bias. *Emotion*, *8*(1), 121–126.

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review*, *11*(1), 192–196.

Waldron, E. M., & Ashby, F. G. (2001). The effects of concurrent task interference on category learning: Evidence for multiple category learning systems. *Psychonomic Bulletin & Review*, *8*(1), 168-176.

Watkins, E., & Teasdale, J. D. (2001). Rumination and overgeneral memory in depression: Effects of self-focus and analytic thinking. *Journal of abnormal psychology*, *110*(2), 353–357.

Weissman, M. M., & Sholomskas, D. (1977). Assessing depressive symptoms in five psychiatric populations: a validation study. *American Journal of Epidemiology*, *106*(3), 203–214.

Wells, T. T., & Beevers, C. G. (2010). Biased attention and dysphoria: Manipulating selective attention reduces subsequent depressive symptoms. *Cognition & Emotion*, *24*(4), 719–728.

Wilson, M.D. (1988) The MRC Psycholinguistic Database: Machine Readable

Dictionary, Version 2. *Behavioural Research Methods, Instruments and Computers*, 20(1), 6-11

World Health Organization. (2012, October 1). Depression Fact Sheet No. 369. Retrieved October 11, 2013, from http://www.who.int/mediacentre/factsheets/fs369/en/

Worthy, D. A., Gorlick, M. A., Pacheco, J. L., Schnyer, D. M., & Maddox, W. T. (2011). With Age Comes Wisdom Decision-making in Younger and Older Adults. *Psychological Science*, *22*(11), 1375–1380.

Worthy, D. A., & Maddox, W. T. (2011). Age-Based Differences in Strategy Use in Choice Tasks. *Frontiers in neuroscience*, *5*, 1–10.

Worthy, D. A., Otto, A. R., & Maddox, W. T. (2012). Working-memory load and temporal myopia in dynamic decision-making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(6), 1640–1658.

Yechiam, E., & Busemeyer, J. R. (2005). Comparison of basic assumptions embedded in learning models for experience-based decision-making. *Psychonomic Bulletin & Review*, *12*(3), 387–402.

Yechiam, E., & Busemeyer, J. R. (2008). Evaluating generalizability and parameter consistency in learning models. *Games and Economic Behavior*, *63*(1), 370-394.

Zeithamova, D., & Maddox, W.T. (2006). Dual-task interference in perceptual category learning. *Memory & Cognition, 34*(2), 387-398.